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Modeling and Control of FES Assisted Standing-up in Paraplegia

by

Rahman Davoodi ©

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of the requirements for the degree of Doctor of Philosophy

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Rahman Davoodi

Department of Mechanical Engineering
Sharif University of Technology
Azadi Ave., Tehran, Iran

January 27, 1999

UNIVERSITY OF ALBERTA

FACULTY OF GRADUATE STUDIES AND RESEARCH

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research for acceptance, a thesis entitled Modeling and Control of FES-Assisted Standing-Up in Paraplegia **submitted by** Rahman Davoodi **in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Medical Sciences - Biomedical Engineering.**

B. Andrews.
Brian J. Andrews (Supervisor)

AW Lipsett
A. William Lipsett

ZJ Koles
Zoltan J. Koles

P.S. Allen
Peter S. Allen

Aleksandar Kostov

RF Zernicke
Ronald F. Zernicke

William K. Durfee
William K. Durfee

Date: January 21, 1999

Abstract

The author has developed a new approach to the design of control systems for Functional Electrical Stimulation (FES) assisted standing-up in paraplegia. The approach is based on machine learning rather than traditional analytical modeling.

The main objective of the study was to investigate the model-free design methods, as it is difficult to develop analytical models of the human body. The results showed that nonlinear FES controllers could be tailored to the needs of an individual patient. The controllers continually adapt to the physical changes and disturbances and are coordinated to the voluntary efforts of the subject.

A sagittal plane model of standing-up was developed including closed-chain configuration and a fuzzy control model of the voluntary arm forces. The model was used in the rest of the thesis for evaluation and comparison of the FES controllers of the knee and hip joints during standing-up.

A comparative study showed that the simple closed-loop controllers outperformed the open-loop controllers but there was room for considerable improvements using nonlinear and adaptive control systems.

Genetic Algorithms (GA) were used to optimize the parameters of the Fuzzy Logic Controllers (FLC) and gain-scheduling PID controllers and produced controllers with superior performance compared to the open-loop and manually designed closed-loop controllers. The voluntary arm forces and the trajectory error were used as the optimization criteria.

Reinforcement Learning (RL) was used for online tuning of the FLC controllers to

minimize the arm forces and the knee terminal velocity. The combination of RL and FLC performed satisfactorily in rejecting the disturbances and adapting to the slow changes in system dynamics.

Finally, the GA was used to generate optimal trajectories tailored to the needs and limitations of the people with impairments such as paraplegia and functionally impaired elderly.

It is expected that these developments in FES control will lead to significant improvements in the clinical applications of FES. The resulting motions will be smoother, safer, and more energy efficient. There won't be a need for continual adjustments by a clinician and the FES controller will become an integral part of the patient's motion control system.

The following articles has so far been published on this work:

1. Davoodi, R. and Andrews, B.J. (1996) A model of FES standing up in paraplegics including upper limb interaction and closed form dynamics. 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam, paper no. 785.

2. Davoodi, R. and Andrews, B.J. (1996) FES standing up in paraplegia: a comparative study of fixed parameter controllers. 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam, paper no. 784.

3. Davoodi, R. and Andrews, B.J. (1997) Modeling and control of FES standing in paraplegia: Possibility of unassisted standing-up. Second Annual Conference of the International Functional Electrical Stimulation Society, Burnaby, Canada, pp. 93-94.

4. Davoodi, R. and Andrews, B.J. (1998) Computer simulation of FES standing up in paraplegia: A self-adaptive fuzzy controller with reinforcement learning, IEEE Trans. Rehab. Eng., 6: 151-161.

5. Davoodi, R. and Andrews, B. J. Optimal control of FES assisted standing-up in paraplegia using Genetic Algorithms (1998) Proceedings of the International Mechanical Engineering Congress & Exposition: Symposium on Dynamics, Control and Design of Biomedical Systems, Anaheim, USA.

6. Davoodi, R., Andrews, B. J., Kamnik, R., and Bajd, T. Neural network model of the voluntary arm forces during FES assisted standing-up in paraplegia (1998) Proceedings of the International Mechanical Engineering Congress & Exposition: Symposium on Dynamics, Control and Design of Biomedical Systems, Anaheim, USA.

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List of Abbreviation

AFO	Ankle Foot Orthosis
ANN	Artificial Neural Networks
ARGO	Advanced Reciprocating Gait Orthosis
CNS	Central Nervous System
COM	Center of Mass
EMG	Electromyography
FES	Functional Electrical Stimulation
FLC	Fuzzy Logic Controller
GA	Genetic Algorithms
GRF	Ground Reaction Force
GRV	Ground Reaction Vector
HGO	Hip Guidance Orthosis
HKAFO	Hip Knee Ankle Foot Orthosis
KAFO	Knee Ankle Foot Orthosis
KEV	Knee End Velocity
KTV	Knee Terminal Velocity
LQG	Linear Quadratic Gussian
LSU-RGO	Luisiana State University Reciprocating Gait Orthosis
MIMO	Multi-Input Multi-Output
MAT	Muscle Activation Time
PID	Proportional Integral Derivative
PNS	Peripheral Nervous System
RGO	Reciprocating Gait Orthosis
RL	Reinforcement Learning
RMSE	Root Mean Square Error
SCI	Spinal Cord Injury
STS	Sit-To-Stand
SU	Standing-up

1 Introduction

1.1 Outline of Thesis

Chapter 1 provides the background to the research within this thesis. Spinal cord injury, its complications, and the current research in the field are briefly introduced. Literature review focuses on standing-up in normal and paraplegic subjects. In paraplegia, both modeling and control of FES-assisted standing-up are reviewed. Different control strategies and techniques employed in this thesis are introduced next with a brief explanation of their philosophy and origins. The thesis hypothesis and specific objectives are developed in this chapter. Objectives of the thesis are stated at the end of the chapter.

Chapter 2 outlines the development of a model of voluntary arm forces during FES-assisted standing-up. Chapter 3 describes the development of a planar model of standing-up in paraplegia, which is used in the rest of the thesis for evaluation of the proposed controllers.

Chapter 4 contains a comparative study of simple fixed parameter controllers when controlling standing-up in paraplegia. In chapter 5, the GA optimization method is used to design optimal FES controllers for standing-up. Chapter 6 describes the use of RL technique to design FES controllers for standing-up.

In chapter 7, the GA is used to generate optimal joint trajectories for impaired standing-up including paraplegia and functionally impaired elderly.

A discussion of all the results and control techniques is contained in chapter 8. This is followed by conclusions and suggestions for further research in chapter 9.

Finally, appendix A formulates the equations of motion for the model of standing-up.

1.2 Spinal Cord Injury

The central role of the spinal cord is to convey sensory and motor functions between the brain and the periphery. Spinal cord injury (SCI) disrupts this communication to the extent depending on the severity of the injury and the segment of the spinal cord at which the injury occurs. The higher the injury is along the backbone, the more movement and sensation will be altered or lost.

1.2.1 Medical Complications

The SCI primarily results in muscle paralysis, loss of sensation, loss of bladder and bowel control, sexual dysfunction, lost or decreased breathing capacity, impaired cough reflexes and spasticity.

SCI can also lead to many secondary complications, including pressure sores, osteoporosis, bladder infections, increased susceptibility to respiratory diseases, and autonomic dysreflexia (Somers, 1992). Autonomic dysreflexia is a potentially life-threatening increase in blood pressure, sweating, and other autonomic reflexes. It is most often caused by bladder outlet obstruction, and rarely by other causes such as bowel impaction, skin sores, menstruation, or labor.

1.2.2 Classification

An accurate and complete examination and classification of the injury is necessary to establish a realistic rehabilitation program for maximum recovery. A complete exam to determine the neurological level involves evaluating both the sensory and motor levels affected by the spinal cord injury. The neurologic level of injury is defined as the lowest segment of the spinal cord with normal sensory and/or motor function on both sides of the body. Levels are numbered C1-C8 in the cervical or neck region, T1-T12 in the thoracic, or chest region, L1-L5 in the lumbar region, and S1-S5 in the sacral region.

The level of spinal cord injury can also be categorized as tetraplegia and paraplegia. Tetraplegia or quadriplegia refers to injuries of the cervical region of the spinal cord that results in partial or complete paralysis of the arms and legs. Paraplegia refers to injuries, which occur in the thoracic, lumbar or sacral segments that spare the arms but affects the legs.

Incomplete injury means the cord has been partially damaged. An incomplete injury has partial preservation of sensation and/or motor function below the neurologic level of injury and includes the lowest sacral segment. A complete injury indicates a complete blockage of nerve messages. With a complete injury, there is no sensation or motor function in the lowest sacral segment.

Upper motor neuron lesion or spastic paralysis refers to SCI patients who preserve segments of spinal cord below the level of injury. The intrinsic reflexes are now uninhibited and become hyper-reflexive and lead to increased muscle tone, spasms, and spasticity. In lower motor neuron lesion or flaccid paralysis, on the other hand, the spinal cord segments below the lesion are not preserved. With this type of injury, the stimuli cannot reach the spinal cord; therefore, the reflexes and muscle tone remain decreased or absent.

1.2.3 Spinal Cord Injury Statistics

Except for the USA, where a national database of SCI statistics is maintained, figures for other countries are inaccurate and vary with the source (Hammell, 1995). The followings are excerpts from "spinal cord injury, facts and figures at a glance", a report published by the national spinal cord injury statistical center in the USA (The National Spinal Cord Injury Statistical Center, 1998).

Incidence and Prevalence: It is estimated that the annual incidence of SCI, not including those who die at the scene of the accident, is approximately 40 cases per million population in the U. S., or approximately 10,000 new cases each year. The number of people in the United States with SCI has been estimated to be between 183,000 and 203,000 persons.

Age at injury: SCI primarily affects young adults. Fifty-six percent of SCI occur among persons in the 16 to 30 year age groups, and the average age at injury is 31.5 years. Since 1973, there has been an increase in the mean age at time of injury. Those who were injured before 1979 had a mean age of 28.6 while those injured after 1990 had a mean age of 34.5 years.

Gender: Overall, 81.9% of all persons in the national database are male. This greater than four-to-one male to female ratio has varied little throughout the last 23 years.

Ethnic groups: A significant trend over time has been observed in the racial distribution of persons in the Model System database. Among persons injured between 1973 and 1978, 77.5% of persons in the database were Caucasian, 13.5% were African-American, 6% were Hispanic, 2% were American Indian and 0.8% were Asian. However, among those injured since 1990 only 56.2% were Caucasian, while 28.7% were African-American, 10.5% were Hispanic, 0.4% were American Indian, 2.1% were Asian and 0.4% were unknown.

Etiology: Since 1991, motor vehicle crashes account for 36.6% of the SCI cases reported. The next largest contributor is acts of violence, followed by falls and recreational sporting activities. Interesting trends in the database show the proportions of injuries due to motor vehicle crashes and sporting activities have declined while the proportion of injuries from acts of violence has increased steadily since 1973.

Neurologic level and extent of lesion: Persons with tetraplegia (51.9%) have sustained injuries to one of the eight cervical segments of the spinal cord; those with paraplegia (46.8%) have lesions in the thoracic, lumbar, or sacral regions of the spinal cord. For the remaining persons, 0.7% recover prior to discharge and 0.6% are persons for whom this information is not available. Since 1991, the most frequent neurologic category is complete paraplegia (28.9%), followed by incomplete tetraplegia (28.6%), incomplete paraplegia (21.8%), and complete tetraplegia (18.4%). Trends over time indicate an increasing proportion of persons with incomplete paraplegia and a decreasing proportion of persons with complete tetraplegia.

Lifetime costs: Average yearly health care and living expenses and the estimated lifetime costs that are directly attributable to SCI vary greatly according to severity of injury (Table 1.1 and Table 1.2). These figures do not include any indirect costs such as losses in wages, fringe benefits and productivity which could average almost $US38000 but vary substantially based on education, severity of injury and pre-injury employment history.

Life expectancy: Life expectancy is the average remaining years of life for an individual. Medical care of spinal cord injury has advanced greatly in the last 50 years. During World War II, injury to the spinal cord was usually fatal, while postwar advances in emergency care and rehabilitation allowed many patients to survive. Paraplegics can now expect a nearly normal life-span, while quadriplegics die 5-20 years earlier, depending on the patient's age at injury and completeness of the injury (Table 1.3 and Table 1.4).

In the past, the leading cause of death among persons with SCI was renal failure. Today, however, significant advances in urologic management have resulted in dramatic shifts in the leading causes of death. The major cause of death in SCI is pulmonary disease, with cardiovascular disease and genitourinary infection in lesser numbers.

Severity of Injury	**First Year**	**Each Subsequent Year**
High Tetraplegia (C1-C4)	$417,067	$74,707
Low Tetraplegia (C5-C8)	$269,324	$30,602
Paraplegia	$152,396	$15,507
Incomplete Motor Functional at any Level	$122,914	$8,614
All Groups	$198,335	$24,154

Table 1.1 Average yearly health care and living expenses. Expenses are in US dollars.

Severity of Injury	**Age at Injury**	
	25 years old	50 years old
High Tetraplegia (C1-C4)	$1,349,029	$876,287
Low Tetraplegia (C5-C8)	$748,234	$528,021
Paraplegia	$427,733	$326,272
Incomplete Motor Functional at any Level	$287,001	$231,018

Table 1.2 Estimated lifetime costs by Age at Injury. Costs are in US dollars.

Age at Injury	No SCI	Motor Functional at any Level	Ventilator Dependent at any Level	High Tetra (C1-C4)	Low Tetra (C5-C8)	Para
20 yrs	56.9	50.2	15.1	32.7	38.1	43.7
40 yrs	38.1	32.3	6.8	18	22.1	26.7
60 yrs	20.9	16.2	1.0	6.5	9.1	12.1

Table 1.3 Life expectancy of SCI patients who survive the first 24 hours.

Age at Injury	No SCI	Motor Functional at any Level	Ventilator Dependent at any Level	High Tetra (C1-C4)	Low Tetra (C5-C8)	Para
20 yrs	56.7	51.2	26.3	36.2	40.1	44.9
40 yrs	38.1	33.1	13.6	20.7	23.7	27.7
60 yrs	20.9	17.3	4.0	8.1	10	12.8

Table 1.4 Life expectancy of SCI patients who survive at least first year post-injury.

1.2.4 Current Interventions and Research

1.2.4.1 Regeneration Research

Scientists have long believed that nerve cells in the central nervous system (CNS) of mature mammalian could not regrow after traumatic injury. This was in sharp contrast with the situation observed in fish, amphibian, mammalian peripheral nervous system (PNS) and immature mammalian CNS which possess significant regenerative capacities and are able to restore neuronal function after lesion (Stichel and Muller, 1998). The pioneering works of David and Aguayo (David and Aguayo, 1981) however, established a new fact that CNS neurons have the capacity to regrow axons given a suitable environment. They showed that lesioned CNS axons grow successfully into a peripheral nerve implant but cease growing as they enter the CNS tissue. Since then an optimistic view has emerged and a number of studies were performed to identify inhabiting factors responsible for axonal regeneration failure and to develop effective experimental strategies to stimulate structural and functional repair of lesioned CNS (Stichel and Muller, 1998).

For successful regeneration to occur following SCI, several things must happen. First, damaged nerve cells must survive or be replaced, despite the acute effects of trauma and the conspiracy of processes that cause secondary damage. Nerve cells that survive the injury often must regrow axons, despite tissue changes such as cavity formation that obstruct growth. Axons also must navigate among the myriad possibilities to find appropriate targets. Once the axons locate their targets, they must construct specialized structures to release neurotransmitters at synapses, while target cells must assemble and precisely locate the structures needed to respond to neurotransmitters. Finally, the neural circuitry may have to compensate for changes that have occurred in the spinal cord circuitry following injury. An extensive research is currently underway to address these issues.

Regeneration studies deserve much attention and may result in new therapies in the future. However, for the present and near future, more research is needed to improve existing strategies, including drug therapy, rehabilitation, and FES. Indeed, the ultimate restoration for some, may be the optimal combination of regeneration, drug therapy, and neural prosthesis.

1.2.4.2 Drug Therapy

Effective drug therapy for spinal cord injury first became a reality in 1990, when methylprednisolone, the first drug shown to improve neurologic recovery from spinal cord injury, moved from clinical trials to standard use. Today, most patients with spinal cord injuries receive methylprednisolone within 3 hours after injury, especially if the injury is severe. A recent study showed that patients with acute spinal cord injury who receive methylprednisolone within 3 hours of injury should be maintained on the treatment regimen for 24 hours. When methylprednisolone is initiated 3 to 8 hours after injury, patients should be maintained on therapy for 48 hours (Bracken et al., 1997).

1.2.4.3 Rehabilitation

The purpose of rehabilitation techniques is to improve patients' health and quality of life by helping them learn to use their remaining abilities. Studies of problems that SCI patients experience, such as spasticity, muscle weakness, and impaired motor coordination, are leading to new strategies that may overcome these challenges (Somers, 1992; Hammell, 1995).

Spasticity, in which abnormal stretch reflexes intensify muscle resistance to passive movements, often develops after spinal cord injury. It may include two separate manifestations: spasms and rigidity that interfere with muscular activity. Several factors may contribute to spasticity but it is commonly attributed to the lack of control from the brain that normally suppresses the spinal reflexes. Current treatments for spasticity include physical therapy, orally medicated drugs such as Baclofen (most common), Diazepam and Valium, injections of botulinum, use of implantable drug pump to administer the drug directly into the spinal cord and destructive neurosurgical procedures to cut the nerves.

The muscle weakness that frequently occurs after spinal cord injury may result from a loss of excitatory signals from the descending tracts. Abnormal patterns of motor activation in muscles may also contribute by making muscles less efficient so that they tire more easily. Restoring normal neurotransmitter signals with drugs may partially relieve these problems. Some muscle weaknesses may also result from abnormal patterns of muscle usage or from changes in muscle properties, including muscular atrophy and growth of connective tissue.

Another motor problem is the lack of muscle coordination that may result in part from the substantial brain reorganization that occurs after injury to the CNS. With a better understanding of how the spinal cord changes following injury, drugs or physical therapy may be used to promote reorganization when it is useful and block it when it is counterproductive.

Rehabilitation strategies will continue to play an important role in the management of spinal cord injury, and they will increase in importance as the ultimate goal of functional spinal cord regeneration is realized. Physical therapy and other rehabilitation strategies also are crucial for maintaining flexibility and muscle strength and for reorganizing the nervous system. These factors will be vital in recovering movement following regeneration as well as maximizing the use of undamaged nerve fibers.

1.2.4.4 Functional Electrical Stimulation

FES is the application of electrical current to elicit muscle contraction for functional control of paralyzed extremities. The effect of electricity in triggering muscle contraction has been known even before the advent of the electricity. For example, touching a torpedo fish, which has special organs that produces an electrical charge to shock its prey, was a well known cause of muscle contraction. Despite these early observations, the functional use of electrical muscle contractions had to await the development of more practical means.

Static electric machines were developed in eighteenth century. The first electric capacitor, known as the Leyden jar, was invented in 1746 to store the charge. Experimenting with this machine, Benjamin Franklin was able to produce involuntary contractions of paralyzed muscles. In 1791, Galvani was the first to suggest, in his theory of animal electricity, the possibility that the muscles and nerves utilize electricity to function. Later in 1800, Volta invented the battery known as the volatic pile but neither static electricity machines nor volatic pile produced sustained muscle contractions. They produced continuous direct current also known as Galvanic current or Galvanism that could induce brief contractions at the moment of circuit closure (Hambrecht, 1992).

Continuous muscle contraction was made possible by Michael Faraday's invention of electromagnetic induction in 1831. This invention brought about the use of interrupted direct current known as Faradic current or Faradism which is still used in today's electrical stimulators. This technology was then employed by Armand Duchenne to restore and maintain muscle function in the middle of the nineteenth century. He is known for identifying the motor points, where the surface electrodes must be placed to contract the individual muscles (Hambrecht, 1992).

The first use of electrical stimulation to restore functional control of a paralyzed limb on a continuing basis is attributed to Liberson and his colleagues. They developed a device to overcome footdrop in stroke patients by stimulating the peroneal nerve (Liberson et al., 1961). A year earlier, Kantrowitz had reported a paraplegic patient with surface electrodes over the quadriceps and gluteal muscles who was able to rise from a sitting to standing position and who was able to maintain the standing position for a few minutes when stimulated (Kantrowitz, 1960). Inspired by Liberson's application, Long and Masciarelli developed a FES splint for control of the hand to perform grasping and releasing in high quadriplegic patients (Long and Masciarelli, 1963). Later developments demonstrated paraplegic patients stand-up and walk using the walking aides (Cooper et al., 1973; Brindley et al., 1979).

These early demonstrations created not only enthusiasm among researchers but also high expectations among SCI patients. Many expected FES systems that would make wheelchairs obsolete. Given the impressive scientific achievements at the time, this did not seem to be out of reach. However, development of the FES systems was hindered by numerous problems. A practical FES system requires safety, reliability, ease of use and implementation, low physical effort, minimal stimulation to reduce muscle fatigue and smooth motions to enhance convenience and endurance. To realize such FES systems, complex control systems are needed to replace the lost control from the CNS. For the highly nonlinear and time-varying musculoskeletal systems, there was no systematic control design method available. The necessity for the FES controllers to interact with the intact part of the patient, i.e., the Man-Machine interactions contributed to further complexity of the problem. Design of sophisticated controllers often require many feedback sensors that are both difficult to mount on the subjects and cosmetically unpleasant. Finally, FES controllers must use, as actuators, the electrically stimulated paralyzed muscles that are in general weaker than normal muscles and can fatigue much faster. It is generally believed that many of these deficiencies may be addressed, at least in part, by improved FES controls.

The need for function restoration depends on the level and the type of the SCI. Quadriplegic subjects primarily need the restoration of function to their upper extremities. Restoration of even a very small portion of the lost function could be very useful in enhancing independence and moral of the subjects. Paraplegics on the other hand, have voluntary control over their upper extremities and some parts of their trunk and can be trained for standing and walking . Similarly, the subjects with incomplete injuries could have different priorities for FES application. Clearly, there are similarities among these categories that makes it possible to use the methods developed for one category in the others. For example, in all cases we have to deal with the paralyzed muscles, sensor problems and Man-Machine interactions. In this thesis however, I will investigate the first stage of the mobility restoration in the thoracic level SCI subjects which is standing-up motion. The previous work relevant to standing-up motion will be reviewed next. A good deal of introductory material on FES principles is now available in the literature (Graupe, 1994; Kralj and Bajd, 1989; Phillips, 1991).

1.3 Review of Literature on Standing-up

Restoration of standing-up in paraplegia has both functional and therapeutic benefits. Functionally, it would allow paraplegics to reach high objects inaccessible from wheelchair, make transactions at a counter and communicate with other people face to face. Standing-up is also a prerequisite to many of the daily life activities such as stepping, transfers and walking and could increase independence, privacy and moral by ruling out the need for an assistant. The functional benefits of standing may be even larger than gait, since, in the foreseeable future, wheelchairs will be used for travelling longer distances. Equally important are the therapeutic benefits from loading the bones, extending the joints, improving blood flow, and activating the muscles that could improve the general health and well being of the subjects (Andrews and Wheeler, 1995; Daly et al., 1996; Graupe, 1994; Kralj and Bajd, 1989; Phillips, 1991).

Standing-up is a dynamically demanding maneuver that requires both higher joint moments and delicate total limb coordination that are absent in paraplegia. Therefore, it is necessary to adopt different strategies to deal with weaker muscles and the lack of control from the CNS. The techniques vary according to the level of injury but the arms are the integral part of the maneuver. In the absence of the control from the CNS, the arms help to provide balance and compensate for the weak joint moments. Therefore, adequate upper body strength is required for standing-up in paraplegia. On the other hand, we can learn from normal standing-up since, it is the strategy perfected by the CNS to perform a safe sit-to-stand transition in various circumstances. In fact, some researchers have attempted to use the joint trajectories or EMG activities of muscles in normal standing-up as the desired patterns to be reproduced in paraplegia (Dolan et al., 1998; Quintern et al., 1989; Kagaya et al., 1995).

1.3.1 Standing-up in able-bodied Subjects

Standing-up is a relatively demanding maneuver performed routinely for the daily life activities. The magnitude of the knee and hip joint moments and their range of motion are greater than those that occur during stair-climbing and walking (Riley et al., 1991; Hughes et al., 1996). The technique usually employed to stand-up from a chair is essentially a sagittal plane maneuver. The maneuver starts with moving the trunk forward over the base of support by flexing the hip and continues with rising by extending the leg joints.

In recognition of the importance of standing-up in activities of daily life, it has been studied from different perspectives. These studies include the definition of events and phases, duration of motion, muscle activity, influence of initial body position, speed of ascent and different strategies in standing-up.

Standing-up maneuver can be divided into phases identified by a set of events defining the transition among the phases. Depending on the measuring equipment and variables used different number of events and phases have been used to describe standing-up. Rodosky et al. (Rodosky et al., 1989) divided standing-up into two phases: the forward-trust phase and extension phase. Nuzik et al. (Nuzik et al., 1986) used two phases, flexion and extension, to describe standing-up. Flexion phase occurred during the first 35% of the movement cycle. Extension phase began by reversal of head movement and a rapid increase in knee extension, which seemed to coincided with lift-off from the chair. Kralj et al. (Kralj et al., 1990) however identified four phases: initiation, seat unloading, ascending and stabilization. Events were identified with a set of descriptive and mathematical definitions using the signals from the force plate, seat switch and goniometers. Schenkman et al. (Schenkman et al., 1990) and Riley et al. (Riley et al., 1991) used four phases but the definitions were different from those of Kralj. The phases were flexion momentum, momentum transfer, vertical extension and stabilization. They used a combination of kinetic and kinematic data to distinguish the events. Pai and Rogers (Pai and Rogers, 1990) identified five events dividing the maneuver into four phases using a force plate under the seat and the movement of the body's center of mass.

Despite using different event definitions, standing-up starts with the first discernable movement of the trunk as it flexes to generate forward momentum. Seat off is the next event that occurs when there is enough forward momentum to carry the subject forward. At this point, momentum transfer takes place. By regulating the extension of the leg joints, the forward momentum of the trunk is continually converted to the vertical momentum that must overcome the gravity. Stabilization is the last phase that takes place at the end of the gross movement of the body.

Duration of standing-up depends on the initial starting position, characteristics of the subject, standing-up strategy and the events defining the start and termination of the maneuver. These events are usually fixed by visual inspection of trajectories or strict mathematical rules. Therefore, it is difficult to compare values reported by different groups. In a study of 55 young adults by Nuzik et al. (Nuzik et al., 1986), movement time ranged from 1.3 to 2.5 seconds and the average time was 1.8 ± 0.3 seconds. The mean duration of normal and arm-assisted standing-up in 12 young subjects studied by Kagaya et al. (Kagaya et al., 1995) were 2.0 and 2.6 seconds respectively. Baer and Ashburn (Baer and Ashburn, 1995) measured the duration in a group of 30 old but healthy subjects. The mean duration to stand was 1.67 sec with a range of 1.26 to 2.13 sec. Inter-subject variations of the timing was significant but each subject was consistent in timing the repeated trials suggesting that there may be a consistency to an individual's timing of the movement.

Biomechanics of standing-up can be affected by initial body position. Investigating the influence of chair design on the biomechanics of standing-up in elderly, Wheeler et al. (Wheeler et al., 1985) found that it was easier to stand-up from a standard chair than the one designed specially for elderly persons. They argued that the greater foot clearance of the standard chair allowed subjects to place their feet further back making it easier to move their center of mass over the base of support. The higher arm rest of the standard chair and the backward tilt of the specially designed chair were the other reasons mentioned by Wheeler. Burdett et al. (Burdett et al., 1985) examined the height of the chair and showed that the higher height substantially reduces the knee and hip joint moments. Shepherd et al. (Shepherd and Koh, 1996) compared the effect of three foot placement, back, preferred and forward, on standing-up. A forward foot placement increased horizontal movement of the center of mass, which was evidenced by increased speed, and amplitude of trunk flexion and the time over which the shank rotated forward. Vertical movement of the body mass resulted in 50% increase in peak hip joint moment. They concluded that forward foot placement would adversely affect the ease of standing-up. Hughes et al. (Hughes et al., 1996) investigated the role of knee strength in the ability of young and functionally impaired elderly subjects in rising from a chair. Their findings showed that the mean isometric strength for the elderly was 103 Nm compared to 276 Nm for the young while the maximum required knee moment was almost the same. Unlike the young subjects that could stand-up from chairs of different height, the number of elderly who failed to stand-up increased with the lower seat height. Since higher knee moment was required in lower seat heights, the insufficient knee extension strength was found to be the cause of failure. Schultz et al. (Schultz et al., 1992) compared the effect of positioning the body segments on easing the lift-off. Flexing the shank to bring the feet under the upper body was the most effective maneuver followed by the forward flexion of trunk, forward stretch of arms and thigh extension. The initial body position therefore, eases rising if it moves the center of mass higher and closer to the base of support.

The effect of rising speed in biomechanics of standing-up was examined by Lowery and Johnson (Lowery and Johnson, 1985). They reported that the joint moment area or angular impulse (the integral of the joint moments over the duration of the maneuver) increases with decreasing speed of rising. Pai and Rogers (Pai and Rogers, 1990) reported that higher speed of ascent decreases the time required to reach the maximum vertical linear momentum of the center of body mass and increases its magnitude but the time to maximum horizontal linear momentum remained invariant. They suggested that different neuromuscular control strategies might be responsible for the control of balance in horizontal direction and changing the potential energy in vertical direction. In another study Pai and Rogers (Pai and Rogers, 1991) reported increase in peak hip flexion moment, knee extension moment and ankle dorsiflexion moment with increasing speed of ascend. According to Vander et al. (Vander et al., 1994), higher speed of ascend shortens the onset of muscle activity but had no significant effect on the relative duration of the phases. Therefore, increasing speed of ascend leaves the phases of the maneuver fairly invariant. Peak leg joint moments tend to decrease with lower speed of ascend but the overall effort required to stand-up increases.

To compare different standing-up strategies, Doorenbosch et al. (Doorenbosch et al., 1994) instructed nine able-bodied subjects to stand-up naturally and with extensive trunk flexion before seat-off. Their results showed that extensive trunk flexion reduced the knee moment but increased the hip and ankle moments. The changes in the knee and hip joint moments were mainly due to the activity of the biarticular muscles. Therefore, the decrease in knee extending moments in the second strategy did not imply a proportional decrease in load of all knee extensors. The effect of extensive initial hip flexion on the reduction of the knee extension moment was also reported by Bajd et al. (Bajd et al., 1982). Riley et al. (Riley et al., 1991) showed that the trunk movement helps in two ways to ease standing-up. First, the forward flexion of the trunk moves the center of mass closer to the base of support at and just after lift-off from the chair. However, this was not the only strategy because, immediately after the lift-off the center of mass was approximately 7 cm posterior to the foot base of support suggesting a statically unstable position. In second strategy, subjects use their upper body to generate forward momentum, which is rapidly transferred to vertical momentum after lift-off. In momentum transfer phase, the activation of the hip joint extensors help to transfer the momentum from the trunk to the thighs which in turn carries the thighs forward, pivoting about the knee joint. This movement results in vertical momentum of the thighs and upper body because, dorsiflexion of the ankle in this phase is minimal. They concluded that trunk makes the most significant contribution to the forward and vertical momentum of the body's center of mass. Riley et al. (Riley et al., 1997) investigated the differences between the successful and failed standing-up maneuvers. They found that "sitback" and "step" failures were caused by insufficient momentum generation that could be due to weakness, impaired coordination or both. Arm-assisted standing-up is usually used by elderly to reduce the demand on the lower extremities. Seedhom and Terayama (Seedhom and Terayama, 1976) compared the knee forces in standing-up with and without the use of arms. As expected, the use of arms to get out of a chair caused a considerable reduction in both the muscle and joint reaction forces. The peak quadriceps force in one subject was reduced from 1265 N to 432 N and the joint reaction force in the direction of tibial axis was reduced from 1875 N to 651 N. Schultz et al. (Schultz et al., 1992) also found that the application of vertical hand force can reduce the required moment in the lower extremity. However, according to their observations in young and old subjects, hands were used to achieve acceptable postural stability at lift-off rather than reducing the required joint moments. Unlike many researchers who have studied the dominant movement of the trunk in sagittal plane, Baer and Ashburn (Baer and Ashburn, 1995), analyzed the movement of the trunk in other planes. In a group of 30 normal adult subjects, they found that the trunk lateral flexion, trunk lateral shift and trunk rotation about the vertical axis were all small compared to the large amounts of forward flexion and upward activity. These results enforce the assumption made by many researchers that standing-up in normal subjects is primarily a sagittal plane motion.

Most of the above studies have focused on standing-up maneuver performed by a healthy or impaired subject. These studies have tried to find explanations and reasons for the observed maneuver and come up with suggestions to improve the performance. None of these studies however, has tried to explore new standing-up strategies that might exist for an individual with specific constraints. It is quite possible that a trunk momentum generated in proper speed and the right time combined with timely momentum transfer techniques could enable a frail elderly to stand-up. Even if such strategies exist, because of their complexity, they may not be known to the subject. Therefore, a method of identifying a set of possible strategies tailored to the constraints of the individual subjects may be helpful in rehabilitation of the impaired individuals.

1.3.2 Standing In Paraplegia Using External Bracing

The conventional rehabilitation method for standing in paraplegia emphasizes orthosis such as the knee-ankle-foot orthosis (KAFO). The typical KAFO has a fixed ankle joint. The knee joint is capable of flexion, but a user controlled lock can fix the knee joint in extended position. KAFO can be worn to stand-up for example from a wheelchair between parallel bars. The subject assumes a position well back in his seat with his hands placed on the parallel bars. He then leans forward and pushes himself vertically upwards. Once up, the subject assumes the 'C' posture by hyperextension of the hip joint (Bromley, 1991). The ground reaction force (GRF) stabilizes the hip joint by passing behind it while KAFO locks the knee and ankle joints.

Other braces extended the stabilization to the hip joint and trunk. They could be worn by higher level paraplegics and potentially offer walking capability. The hip guidance orthosis (HGO), hip knee ankle foot orthosis (HKAFO), the Louisiana State University reciprocating gait orthosis (LSU-RGO) and the advanced reciprocating gait orthosis (ARGO) are in this category (Douglas and Larson, 1983; Lotta et al., 1994; Rose, 1979). Apart from walking capabilities all three orthosis can be used for standing-up by employing a technique described above for KAFO.

Despite the continual improvement in the long leg braces, they are bulky, cumbersome, difficult to don and doff, and inefficient. In a study of 98 paraplegics patients who were fitted with KAFO, 16 used them for functional walking, 25 for exercise walking or standing, and 57 did not use them at all (Coghlan et al., 1980).

1.3.3 Standing-up In Paraplegia Using FES

FES assisted standing-up was first demonstrated by Kantrowitz (Kantrowitz, 1960) in 1960. The quadriceps and glutei muscles of a paraplegic subject were stimulated using surface electrodes. The patient was able to stand-up and maintain standing for few minutes. Similar method was used later by Wilemon et al. (Wilemon et al., 1970) and Reswick (Reswick, 1972). Femoral and gluteal nerves were stimulated by the implanted stimulators to contract the knee and hip joint extensor muscles. A T-5 female paraplegic patient was able to stand. The ankle joints were stabilized by short leg ankle braces.

The above mentioned studies were single trials that demonstrated the feasibility of standing in paraplegia using FES. More comprehensive study of standing-up in paraplegia was carried out by Kralj, Bajd and associates (Bajd et al., 1981; Bajd et al., 1982; Kralj et al., 1980; Kralj and Bajd, 1989). They showed that all the subjects with lesion above T-12 have leg muscles, which are electrically excitable and standing-up can be achieved using surface electrodes. They proposed a procedure, now widely adopted clinically, for standing up using upper body assistance and bilateral stimulation of the knee extensors (Bajd et al., 1982). The knee extensors were stimulated with a preset constant level stimulus in an open-loop manner (Figure 1.1). This technique or a modified version (that linearly ramps-up the stimulation from zero to the preset maximum level) were adopted by other research groups and are still in use. Although the technique is simple and works adequately for many people, it is deficient in many aspects.

The method works because, most of the paraplegics with strong arms can lift themselves and stand-up with little or no help from the lower extremity muscles. The arms can generate enough force actions that could compensate for and possibly hide the deficiencies in the FES control system. To play such a role, the arms must produce significant amount of force actions that can exceeds two-thirds of body weight (Dolan, 1997; Kamnik et al., 1997). The latter is of concern because over time the cumulative effects of transfers and wheeling can cause or exacerbate arm injury and pain due to overuse. Among 94 patients with complete paraplegia studied by Bayley, et al. (Bayley et al., 1987) 31 reported chronic persistent shoulder pain on transfers that was clinically diagnosed as rotator cuff impingement syndrome. High arm forces are also the cause of fast fatiguing in the upper extremities that usually discourage the patients. Bajd et al. (Bajd et al., 1984) showed that paraplegic standing endurance is highly correlated with the upper body support forces.

Preset constant level stimulation also results in a pattern of knee extension torque that differs significantly from the normal profile in which initially, a high peak torque is generated to lift-off the seat, is then followed by a progressive reduction in torque as the knee extends (Doorenbosch et al., 1994; Kelly et al., 1976). Therefore, there is an excess of stimulation that contributes to muscle fatigue and higher than normal knee end velocity (KEV). High KEV may be a concern since it is not known if such repetitive insults to the ligaments may ultimately lead to damage as it is the ligaments that absorb all the energy in bringing the leg to a rapid and jerky halt.

It is believed that many of these problems can be solved by improved control strategies. A number of researchers using simulation studies or experimental trials suggested improvements to the open-loop control method of Bajd and Kralj.

Since, standing-up is primarily a sagittal plane motion, most of the models are two dimensional and are confined to sagittal plane. Both inverse and forward dynamic models are used depending on the objectives of the study.

Inverse dynamic models are used to calculate the internal forces and moments in the joints and muscles from the measurement of the kinematics and the external forces. Inverse dynamic models are easier to develop because one limb is considered for analysis at a time. Once the motion and external forces (hand or ground reaction forces) are measured, the only additional requirements are the geometrical and inertial properties of the limb. Internal forces can be computed by applying simple moment and force equations for dynamic equilibrium of one limb.

Forward dynamic models predict the motion of the system given the applied forces and initial conditions and are used to investigate different scenarios and motion control strategies. However, the accuracy of the predictions depend on the accuracy of the elements forming the forward dynamic model. These elements include the geometrical and inertial properties of the limbs, equations of motion for multi-limb system, passive resistance of the joints, models of muscle actuation and fatigue, muscle geometry during motion, etc. The situation becomes much more difficult when a control design process requires us to obtain the model parameters from a live person. Therefore, in practice, many assumptions must be made to develop forward dynamic models that may compromise their prediction accuracy. Although, accurate forward dynamic models are difficult to develop, even approximate models are useful in comparing different scenarios, sensitivity analysis, initial design of controllers or investigating the feasibility of a novel idea which is unsafe to test, for the first time, in experimental settings.

The controllers for early standing-up trials were simple open-loop methods. As mentioned earlier, the most popular method proposed by Bajd and Kralj was simple but deficient in many aspects. Therefore, new control strategies were developed to improve the performance of the FES assisted standing-up.

The following is a review of the research efforts relevant to the modeling and control of standing-up in paraplegia.

Petrofsky (Petrofsky et al., 1984) used a linearly increasing stimulus intensity to perform standing-up. Fast open-loop ramp-up of knee extensors, extended the knee joints to bring the patient to standing position (Figure 1.1). The measured knee angle was used to detect full knee extension and standing when the stimulation was set to a preset level required to prevent the knee buckling. *Minor improvements were observed compared to the simple open-loop control with maximum preset stimulation.*

Jaeger (Jaeger, 1986) investigated the closed-loop control of ankle joint to restore quiet standing (no arm support) in paraplegia. A three-link static model including shank, thigh and head-arm-trunk was developed. The model was restricted to sagittal plane and provided information regarding the distance between the GRF and the joint centers. This information was used to define eight modes of standing depending on weather the GRF passes in front or behind the joint centers. In another study they found that only two of these modes are usually used, GRF behind hip and knee but in front of ankle or GRF behind hip but in front of knee and ankle (Jaeger et al., 1989). They also developed a single-link inverted pendulum dynamic model to evaluate the use of closed-loop PID controller to regulate the ankle joint. They assumed that both the knee and hip joints are stabilized in extension and only ankle joint was free to move. The electrically stimulated muscles around the ankle joint was represented by a second order model. Quiet standing could be achieved within certain limits subject to biomechanical constraints and to the available torque produced by the stimulated muscle. The controller was robust to ±20% variations in gain and pole locations of muscle model and a disturbance of 70 Nm torque pulse in the ankle joint.

Jaeger et al. (Jaeger et al., 1989) reported on 21 paraplegic patients standing with a two channel stimulator. Standing-up was performed by linearly ramping-up the stimulation intensity of the quadriceps from zero to a predefined maximum level in 2 seconds. Upon assuming upright posture, the 'C' posture was assumed by hyperextension of the hip joint and the quadriceps stimulation was kept at maximum level to stabilize the knee joint. No results on the performance of the standing-up maneuver were given but the subjects were able to stand for periods of up to 30 minutes.

Ewins (Ewins et al., 1988) employed PID controllers to control the position of the knee joint during standing-up. The desired knee joint trajectory was a linear ramp up of the knee angle from flexion to full extension in a period of 8 seconds. This is not similar to normal standing-up trajectories often used as the target and no explanation was given on why it was chosen in this study. Although it is claimed that the results were satisfactory, no data on performance of the PID controller were given. *They reported that one set of control parameters was not sufficient for standing-up and standing because, faster response was required in the latter.*

Andrews et al. (Andrews et al., 1988) used a rule-based controller to regulate posture during standing. Standing-up was performed by ramping up the stimulation intensity to the quadriceps muscles in an open-loop manner. Once standing, the rule-based controller regulated posture by detecting either the knee buckling or the position of the GRF from the knee joint. They argued that the required knee extension moment depended on the position and magnitude of the GRF and the subject's posture. In the first strategy, the quadriceps muscles were stimulated after detecting a knee buckle, which was detected using a flexible goniometer. The second strategy was based on estimating the distance from the GRF to the knee joint. Stimulation to the quadriceps was turned on before GRF moved to the back of the knee joint. This was preferred to the first strategy because it acted in anticipation of the knee buckling while the first strategy acted only after buckling occurred. In comparison to the open-loop control, a considerable increase in duration of standing was achieved. A rigid ankle foot orthosis (AFO) was also used to stabilize the ankle joint. In another study (Andrews et al., 1989), Andrews argues that restricting ankle dorsiflexion by natural causes or external bracing helps to stabilize the knee joint and therefore, reduce the need for the knee extension moment. Mulder et al. (Mulder et al., 1992b) explained that restriction on ankle dorsiflexion increases the ankle moment which moves the GRF further forward. Increased distance from GRF to the knee joint develops an increased extension moment at the knee joint which helps to lock it.

Closed-loop finite state control similar to the first strategy employed by Andrews et al. (Andrews et al., 1988) was also used by Mulder et al. (Mulder et al., 1992b) to prevent the knee buckling during standing. Hip joint was mechanically stabilized and the ankle joints were either free or stabilized by AFO. Compared to open-loop control, standing duration was increased as much as 2.5 to 12 times and the torque loss was limited. *Finite state control however induced a limit cycle oscillation in the knee joint, which was a cause of subject discomfort. Although, the closed-loop on/off control has made notable improvements, it might be possible to improve performance and comfort by introducing better control algorithms. The use of AFO was found to reduce both the average arm support and the maximum knee flexion by half. These results are clearly in favor of using AFO during standing but it is not known if they are also useful during standing-up.*

Quintern et al. used a three-link inverse dynamic model of human body to calculate joint torques during standing-up and sitting down in five healthy subjects (Quintern et al., 1989). They reported that the total knee joint moment for both legs in lift-off from the chair was in the range 70-140 Nm depending on the weight and movement characteristics of the subjects. This was also the maximum knee joint moment that was reduced continuously to a minimum in standing position. Since two of their paraplegic subjects could produce only 40 Nm of knee extension moment in each leg when stimulated electrically, they concluded that some patients may need to use their arms during the push-off period of standing-up and the last second of sitting-down. *These comparisons seem to be invalid because they can be made only when the paraplegics can mimic the strategy employed by the normal subjects. Standing-up in normal subjects makes use of momentum transfer techniques and the maneuver could go through statically unstable situations. Because of the lack of proper coordination, paraplegics can only assume statically stable situations and can not take advantage of the momentum transfer techniques. Therefore, despite the predictions of Quintern et al., paraplegics need their arm support for both vertical lift and balance*. They also compared simple open-loop and closed-loop control of standing-up and sitting-down. Both quadriceps and gluteal muscles were stimulated. The stimulation to the gluteal muscles was ramped in an open-loop manner while the quadriceps muscles were controlled using either open-loop or open-loop plus closed-loop controllers. The open-loop part of the stimulation was either a simple ramp up or ramp down of the stimulation intensity. The closed-loop part was a PID controller, which was supposed to follow knee joint trajectory similar to that in normal subjects. They found that the performance of the open-loop control was very dependent on the coordination between the subjects' voluntary efforts and deliverance of the electrical stimulation. *They reiterated the generally believed idea that the voluntary control of upper body must be synchronized to the artificial control of the paralyzed lower extremities.* The pure feedback control was unstable because high feedback gains were needed. Their best results were achieved using both open-loop and closed-loop controllers together and this was more advantageous in achieving a controlled sitting-down motion. Integral term was switched off because it mostly deteriorated the stability. In general high controller gains were required that in turn caused some oscillations. *This is because of the dynamics of standing-up where, the knee extensor muscle torque must be regulated within a wide range. The required torque changes from a maximum in push-off to a minimum in standing. Therefore, high feedback gains are required in push-off phase that will inevitably cause oscillations at later stages of the motion.*

Khang and Zajac (Khang and Zajac, 1989a; Khang and Zajac, 1989b) developed a planar forward dynamic model of unassisted standing in paraplegia. The model included foot, shank, thigh and trunk-head and assumed that the feet were flat during the motion. Thirteen muscles at the hip, knee and ankle joints were simulated; assuming that, each muscle is controlled separately by implanted electrodes. Forces due to the arm movements were treated as external disturbances and simulated by horizontal force, vertical force and a moment acting at the shoulder joint. The model was then linearized about the vertical setpoint corresponding to the quiet standing. The linearized model was used to design an optimal linear feedback control to maintain standing by activating 13 muscles in the lower extremities. The controller gain matrix was obtained by minimizing a cost function that included a weighted sum of angular deviations from vertical, angular velocities and muscle torques. The controller used the error from the desired vertical position and the controller gain to find the corrective joint moments. A static optimization method was then used to distribute each joint's required moment among the muscles acting on that joint. The original nonlinear model was used to evaluate the performance of the controller. Disturbances to the quiet standing were simulated by cyclic arm movements, forward arm raise and initially flexed joint angles. The controller was able to recover from slightly flexed position (8° flexion at knee, hip and ankle) and more flexed position (40° flexion at knee and hip) simulating standing-up. The latter however was midway between sitting and standing position and no explanation was given on why it was chosen as sitting position. The minimization of energy resulted in interesting muscle activation patterns that avoided coactivation of antagonistic muscle pairs and preferred the activation of fast and stronger muscles to slower and weaker muscles in each agonist group. It was suggested that these patterns could be used as simpler alternatives to computationally expensive static optimization. It was also found that due to kinematic coupling each muscle significantly accelerates not only the segments to which it attaches but also the other segments. *The control strategy employed here relied on a linearized model of standing about the vertical position and might not be able to recover from higher disturbances than those simulated here. This might be the reason why the standing-up was performed starting half way between sitting and standing. The muscle forces did not consider the weakness of the electrically stimulated muscles and fatigue. Weaker muscles could easily saturate and severely limit the performance of the proposed controller. The passive joint resistance, which was ignored in this study, seems to be important as the knee and hip joints operate in their anatomical limits. As with other model-based methods, it will be very difficult to estimate the very extensive model parameters required by the model, especially for a living person. The model developed by Khang and Zajac however, was one of the best models of standing in paraplegia and helped to gain valuable insight into the system.*

A three-link forward dynamic model including shank, thigh and trunk was developed by Mulder et al. (Mulder et al., 1992a) to evaluate open-loop and closed-loop on/off control (based on a phase plane switching curve of the desired knee velocity versus knee angle) of standing-up. The shank was assumed to remain vertical. The rotation of trunk was tied to that of thigh so that it was always half the rotation of thigh. Arm force was modeled as vertically directed constant force and horizontal arm force was ignored. Because of these simplifications, knee angle could completely determine the position of the whole system. The model was used to determine the sensitivity of the system to muscle dynamics and unknown arm forces. If knee extensors could produce 75 N.m per leg, and starting from knee angle of 90°, a minimum of 250 N arm force was required for standing-up using open-loop control. With no arm force, standing-up was possible only starting half way, i.e., knee angle of 45°. For higher arm force than 250 N, KEV increased (linearly) and muscle activation time (MAT) decreased. For arm forces of 250 N and 500 N the KEV and MAT were (189 °/sec, 4.3 sec) and (235 °/sec, 1.0 sec) respectively. The use of closed-loop on/off control reduced both the KEV and MAT over the range of arm forces and muscle response time. *The proposed model revealed some interesting results about the sensitivity to parameters and comparing two strategies but as with other forward models the results could not be confirmed by experimentation. Such a confirmation requires a subject with similar physical properties to stand-up from similar initial condition with similar activation of the legs and upper body muscles without interfering internal and external disturbances. This is off course impossible and therefore, forward dynamic models are most useful in sensitivity analysis and comparative studies to determine the merits of one strategy when compared to the other. However, the prediction accuracy of the forward models can be improved by developing models that are more realistic. The model proposed here was apparently deficient mainly because of neglecting horizontal arm force, neglecting the geometric constraints imposed by the arms, neglecting the passive joint resistance, assuming constant vertical arm force and binding together the motion of thigh and trunk.* They also used a stand-up apparatus to compare the controllers where, the paraplegic subject laid in supine position to simulate standing-up. A linear switching curve with zero final velocity was used (Figure 1.2). In the closed-loop strategy, the stimulation to the knee extensors was turned on/off by comparing the actual knee velocity and angle to the switching curve. When using open-loop control in one subject, the KEV and MAT were 515 °/sec and 0.74 sec respectively. Closed-loop control reduced both KEV and MAT by 40% and 70% respectively. Although the arm force was not measured, they predicted that it would increase because the duration of motion was increased considerably. However, they gave a higher priority to the KEV arguing that the duration of standing-up maneuver is small compared to standing. *This interpretation ignores the possibility that the required maximum arm force might be difficult to produce or dangerous in frailer subjects. Therefore, it might be necessary to minimize the maximum arm force, the total energy expenditure by the arms or both. The results of the second subject were highly irreproducible and were not presented. Even in the first subject, the results were irreproducible but variations were smaller. The existence of high variability in such a controlled environment shows how difficult it is to compare the results among different experiments and different subjects.*

Activity patterns of the lower extremity muscles in normal subjects were used by Kagaya et al. (Kagaya et al., 1995) to restore standing-up in paraplegia. In a group of 12 normal subjects, the EMG activity patterns and the maximum knee moments were measured during unassisted standing-up. The EMG patterns were approximated by trapezoids and were then normalized. The normalized EMG patterns were scaled to the maximum knee moment to obtain the required knee moment in paraplegia. Finally, isometric knee moment was used to obtain the stimulation intensity required to produce the knee moment patterns. Similar procedure was used for the other muscles but this time the EMG pattern belonged to arm-assisted standing-up in normal subjects. They reported that the two paraplegic subjects could stand-up smoothly but the results were not compared to the established open-loop control of standing-up. *They reported an initial knee flexion at the start of motion and attributed it to the lack of synchronization between the patient and the FES. This is always true specially for the open-loop control used in this study. A smooth standing-up maneuver in paraplegia can only be obtained when there is a good coordination between the FES and the voluntary efforts of the subject. Another likely reason for the initial knee flexion is the lower stimulation in the first leg of the trapezoid, which in combination with the neurotransmission delay could postpone the development of the knee moment. The procedure employed in this study uses many assumptions to extract the knee moment in paraplegia standing-up from essentially dissimilar movement in normal subjects. Therefore, it is not clear if the calculated knee moment is appropriate for the arm-assisted standing-up in paraplegia. The authors have not proposed a method* *for solving the actuator redundancy, i.e., it is not clear how they assign the share of the multiple muscles acting on a joint. The inverse isometric curve was used to determine muscle stimulation intensity. This approach is invalid because muscle activation during standing-up is not isometric, there is a considerable neurotransmission delay, and muscle force is affected by fatigue.*

Fujita and associates studied an open-loop stimulus adjustment for maintaining upright standing in paraplegia (Fujita et al., 1995). Using a three-link static model, an upright posture was selected to minimize the squared sum of the leg joints' moments. The arm support force was assumed to be zero in the calculations. The selected posture as the result of optimization, was similar to that of the able-bodied subjects. To obtain such a posture in paraplegic patients, a manual procedure was used to determine the stimulus intensity of the muscles to produce the required moments. The procedure was applied to patients lying in the supine position and they tried not to use the biarticular muscles unless necessary. The subjects could stand for 30 minutes and the relative position of the joints with respect to the GRF was similar to that of the able-bodied subjects. The joint moments were different from that of the able-bodied subjects especially in the ankle joint. The lower ankle dorsiflexion moment in paraplegia resulted in more vertically oriented shank position. Although the joint moments in able-bodied standing was used as the desired reference, of necessity, the joint moments in paraplegic subjects were different. Because, ankle joint was not stimulated to avoid spasticity and knee moment was increased to obtain a level of safety. To avoid the constant stimulation of the knee joint, the authors suggested using a closed-loop control. Further, the use of arms by the paraplegic subjects is expected to affect the predictions of the model that ignored the arm force. *The suggested control method is open-loop and incapable of responding to internal (muscle fatigue) and external (arm force) disturbances. The authors tried to avoid using the biarticular muscles because their actions are too complex to be harnessed by manual adjustments. The same is true for stimulation of the nerve roots that affect many muscles and joints. Therefore, a control design method is desirable if it could unravel the complexities of the muscle actuators and use them to perform useful functions.*

Donaldson and Yu (Donaldson and Yu, 1996) proposed a controller for minimizing the handgrip reaction forces during standing-up. They suggested using the measurement of the hand reaction forces to calculate the equivalent leg joint moments to unload the arms. Static equilibrium and left-right symmetry were assumed for calculations. Inverse models of the muscle recruitment curves were needed for calculation of the appropriate muscle stimulation levels. *As mention by the authors, reducing the arm force does not necessarily warrant the global optimality. The dynamics of the motion is ignored and it remains to be seen how this omission affects the performance of the proposed control system. The most important drawback might be the reliance on muscle models that are difficult to obtain for a living person. These models should not only include fatigue but also be invertible. It is also necessary to address the actuator redundancy in assigning the share of the individual muscles in the requested joint torque.*

Feedback control of unassisted standing in paraplegia was investigated by Hunt et al. (Hunt et al., 1997) and Munih et al. (Munih et al., 1997). The body above the shank was braced so that the subject was only free to move about the ankle joint. The resulting configuration was modeled by an inverted pendulum actuated by electrically stimulated ankle muscles. A nested-loop linear quadratic gaussian (LQG) controller was used with inner loop regulating the ankle moment and the outer loop regulating the ankle angle. The reason for choosing a nested structure was its robustness as the inner loop serves to neutralize the nonlinear effects of the muscles. The controller was tested on a healthy and a paraplegic subject. Unlike the results of the healthy subject, that showed a good tracking performance within 1.5-3°, the results of the paraplegic subject was unsatisfactory. Muscle weakness, fatigue and spasticity were found responsible for less stability, asymmetry in left and right legs' motion and saturation of the muscle actuators. *Simplifications were made to an inherently nonlinear system so that a linear controller could be developed. Even in such a simplified situation with limited range of motion, the controller was unable to handle the well-known limitations of FES, i.e., fatigue and spasticity. Therefore, more complex motions such as standing-up with a higher range of motion, nonlinearity and voluntary interactions would certainly be out of reach of such a linear controller.*

Riener and Fuhr (Riener and Fuhr, 1998) developed a three-segmental forward dynamic model of human body including shank, thigh and upper body to evaluate FES controllers for standing-up. Nine mono and biarticular muscle groups were modeled in the sagittal plane inducing moments about ankle, knee and hip joints. The active moment developed by a muscle group in response to electrical stimulation was calculated by taking into account the muscle's moment arm about the joint, force-length and force-velocity relationship and maximum isometric muscle force. Total moment about a joint was the sum of active, passive elastic, and passive viscous moments. The contribution of the arms during standing-up was simulated with forces and moments acting at the shoulder joint. Fuzzy logic controllers were used to model these forces and moments. The Fuzzy controllers were designed to follow shoulder joint position and trunk orientation observed in a paraplegic during arm only standing-up. They also developed an inverse dynamic model by inverting the equations of motion of the forward dynamic model. Some simplifications were made to make the inversion possible. For example, time delay and muscle fatigue were neglected in inversion. Given the desired joint kinematics and external forces, the inverse model calculated the required stimulation intensities of the muscle groups. The muscle actuator redundancy was resolved by a linear optimization algorithm. The forward and inverse models were used to evaluate two controllers. The first was a controller proposed by Donaldson and Yu (Donaldson and Yu, 1996) that maps the measured handle reaction forces to the equivalent leg joint moments and stimulates the leg muscles to eliminate or reduce them. The second controller proposed in this paper was also intended to unload the arms but instead of using the arm force measurement, the actual kinematics of the joints were used to calculate the joint moments necessary to produce the same kinematics. The resulting motion in both cases were similar and reduced the arm forces compared to the arm only standing up without FES. The results however, were not compared to the open-loop control of standing-up. In the first strategy, oscillations in the balancing arm force, which was directly used in determining the stimulation intensities, affected the quality of the resulting motion. The main problem with the forward dynamic model was that the fuzzy control model limited the shoulder position and trunk orientation to those observed in a paraplegic person. *It is known that if the position of shoulder and orientation of trunk are fixed, the sagittal plane* *configuration of the legs will be completely defined. Therefore, the whole motion will be dictated by the fuzzy model of the arms irrespective of the FES control strategy. A realistic arm force model should be flexible and responsive to the FES controllers' actions. Further, the many parameters of the model were obtained from different literature and it was not clear how they might be found for an individual. This is not very important as long as the forward dynamic model is used in comparison of different control strategies, sensitivity analysis to parameters or initial design of the controllers. However, this becomes more serious when the controller design and operation relies heavily on the model, which is the case for the inverse dynamic model here. Certainly, the many detailed model parameters used in the controllers can not be obtained for a living person. Even when an accurate model is obtainable, other problems could significantly deteriorate the performance of these controllers. First, the accurate musculoskeletal models are very complex and computationally costly for real-time implementation. This is especially true for the optimization process employed in this study to solve the muscle actuator redundancy. Second, there is a considerable time delay in the muscle actuation that can not be inverted. Therefore, any control action will be late, at least, as long as the neurotransmission delay. This might introduce oscillations and instability to the system. Third, due to the muscle weakness, the required joint moments might not be attainable which could result in insufficient control. Finally, well-known problems of FES control, i.e., muscle fatigue and spasticity could further deteriorate the performance of the proposed controllers.*

Switching curve closed-loop on/off control was compared to the open-loop control of standing-up and sitting down by Dolan et al. (Dolan et al., 1998). The objective was to reduce the arm force and the KEV. Arm assistance and bilateral stimulation of the knee extensor muscles were used to perform the maneuver. The switching curve described the desired knee velocity as a function of the knee angle with a second-order polynomial based on the measurements from the able-bodied subjects (Figure 1.2). The closed-loop control was found to cause oscillations at the start and termination of standing-up and start of sitting-down. For standing-up, closed-loop control increased both the duration and arm support force while the stimulation was decreased and the KEV data were inconclusive. For sitting-down however, closed-loop control significantly reduced the termination velocity. *Therefore, the proposed closed-loop control did not offer any advantages over the open-loop control for standing-up but, it was better in providing a controlled decent in sitting-down.*

Matjacic and Bajd (Matjacic and Bajd, 1998a; Matjacic and Bajd, 1998b) proposed a control strategy for maintenance of unassisted standing that was based on residual sensory and motor capabilities of the paraplegic subjects. They did not design a complex controller but instead let the subject's CNS do the job. However, they helped by providing the CNS with a simplified system that was controllable. Knee and hip joints were kept in extension by external bracing or FES, and the arms were kept crossed on the chest. The subject was therefore constrained to sagittal plane with two degrees of freedom at ankle and lumbosacral joints. The ankle joint was assumed to have a fixed stiffness provided by passive resistance, FES, mechanical spring or a combination of them. The lumbosacral joint was however under voluntary control and the CNS was supposed to figure out an strategy to keep the balance of this underactuated system during standing. This was only possible if the actuation of trunk motion could stabilize not only the lumbosacral joint but also, by the help of dynamic coupling, the ankle joint. A modeling study (Matjacic and Bajd, 1998a) using a double-link inverted pendulum revealed that it is feasible for a linear fixed parameter CNS controller to maintain balance, using the trunk angle as feedback, if the ankle stiffness is selected properly. Experimental evaluation (Matjacic and Bajd, 1998b) showed that a T-12 paraplegic and a normal subject could maintain standing and that their control performance were improved over four days of training. The ankle stiffness of 8 Nm/° was found to be adequate for comfort standing. When disturbed in the ankle joint, both subjects used similar strategy for recovery. A cognitive auditory feedback, signaling to the subject the position of the ankle joint, improved the robustness of the control strategy and made even the "blindfold standing" possible. *The results in this study show the flexibility and plasticity of the preserved voluntary control. It also shows how the voluntary control might be used to perform useful functions when synchronized to the artificial control. Here, the artificial control was very simple and only provided a fixed stiffness in the ankle joint. Then all the* *learning and control was left to the CNS. Maneuvers such as standing-up will need a more sophisticated artificial FES control if such synchronization with the voluntary control is desired. The learning capabilities of the CNS are well known. However, what is not known is whether an artificial controller can be designed to adapt itself to the CNS. In this case, the learning will be mutual, i.e., the CNS adapts itself to the artificial controller and vise versa.*

1.4 Thesis Hypothesis

The review of the literature on modeling and control of FES assisted standing-up in paraplegia, revealed many areas in which, further research is necessary to improve on the existing procedures. I believe that the followings are the most important areas, in need of further research:

1. It has been difficult to develop accurate models of FES assisted standing-up in paraplegia. Difficult elements to model included the voluntary control of the arms, muscle activation dynamics, passive joint resistance, skeletal geometry and physical parameters of the patients. It was especially difficult to tailor the models to the specifications of a living person. Unlike the other elements, no attention has been given to the modeling of the voluntary arm forces and there is a need for the models representing the voluntary control of the individual subjects.

2. Some ad-hoc and simple controllers have been used but they have never been compared to each other. Because of the considerable inter-experiment and inter-subject variations, such a comparison can not be made using the experiments on patients. Therefore, a controlled environment such as a realistic model must be used to compare different control strategies.

3. The control methods based on the analytical models of the controlled system had little success in FES standing-up because the accurate models could not be developed or the models were too complex to control. Therefore, such controllers so far, have been

applied to simple scenarios with limited success. Therefore, there is clearly a need for model-free methods of designing FES controllers for standing-up.

4. The quality of FES standing-up strongly depends on the existence of coordination between the artificial FES controller and the voluntary control of the subject. Therefore, a control design methodology is needed to obtain such coordination.

5. Because of the considerable inter-subject variations and non-stationary nature of the dynamics of FES standing-up, there is a need for a controller that could adapt to the specifications of an individual and could also compensate for the time-variations in the subject.

6. Safety, convenience, endurance, user-friendliness and in some cases, even the possibility of FES standing-up, depends on the optimization of the limited resources available to the patient. Therefore, a control design method is needed to find, among the many possibilities; those control strategies that take into account the constraints of the patient and optimize the objectives relevant to the quality of standing-up.

7. Normal and impaired standing-up has been analyzed to mainly find the reasons for an existing condition or impairment and there is a need for a procedure to explore the new compensatory standing-up strategies for people with impairments including paraplegia and functionally impaired elderly.

To address the above mentioned gaps in the literature, I hypothesize that:

H-1. Accurate ANN models can be developed to represent the voluntary control of the arms, in FES assisted standing-up in paraplegia. Such models can be tailored to the specifics of a patient.

H-2. A model of standing-up, although a simpler representation of the reality, is an appropriate tool for evaluation and comparison of different control strategies in a controlled environment.

H-3. Controllers for FES assisted standing-up can be developed without requiring a model of the controlled system.

H-4. Such a model-free design method can achieve Man-Machine coordination by synchronizing the artificial FES controllers to the voluntary control of the subject.

H-5. Such a model-free methodology can use the so-called "hardware-in-the-loop" approach where control is learned by direct interactions with the system. By doing this, it can optimize the controller to the specifications of the subject and continue the adaptation to compensate for the time-variations.

H-6. There exist machine learning techniques including RL and GA, which in combination with nonlinear function approximators such as the ANN and FLC can realize 3-5 above.

H-7. The GA is a capable optimization method that can be used to explore the optimal standing-up trajectories for an impaired person. It can account for the impairments and weaknesses of the person by finding alternative compensatory strategies.

1.5 Control Strategies Adopted in this Thesis

Both conventional and new machine learning control techniques are used throughout the thesis to control the delivery of electrical stimulation to the paralyzed muscles. The common property of these controllers is that they are all model-free methods. Therefore, there is no need for a mathematical model of the system, which is usually the difficult part of the control design process. This is especially important for the musculoskeletal systems that are difficult to model with accurate mathematical equations. In this thesis however, a simple model of standing-up is developed to demonstrate the feasibility and compare the merits of the proposed control techniques. Therefore, the model is used as the virtual patient and no knowledge of the model is used in the design of the controllers. The control techniques considered in this thesis are introduced in the following sections.

1.5.1 Open-Loop control methods

By definition, open-loop control systems deliver a pre-programmed sequence of electrical stimulation to the muscles without monitoring the actual state of the system. The stimulation can be delivered in a simple on/off manner preset to a maximum level, obtained by trial and error or obtained using a dynamic model of the system. Since the actual state of the system is not monitored, the open-loop control is susceptible to internal and external disturbances such as muscle fatigue and voluntary arm forces. Because of their simplicity, different forms of open-loop controllers have been used in FES assisted standing-up (Bajd et al., 1982; Kralj and Bajd, 1989; Petrofsky et al., 1984; Jaeger et al., 1989; Kagaya et al., 1995; Fujita et al., 1995).

Two simple but commonly used open-loop control methods are selected for evaluation (Figure 1.1). First open-loop control strategy applies a preset constant level stimulation to the knee extensors during the whole duration of standing-up and standing. The method was first introduced by Bajd et al. (Bajd et al., 1981; Bajd et al., 1982) but was later duplicated in many FES laboratories. Because of its common use, it is often used as a basis to compare the merits of the other control methods.

The second open-loop control strategy, linearly ramps-up the stimulation to the knee extensors from zero to a preset constant level. The stimulation is then kept constant at the preset level. This method is also used by many FES groups and is described by Petrofsky (Petrofsky et al., 1984).

1.5.2 Proportional Integral Derivative Controller

PID controller is probably the most commonly used controller in feedback control systems. The PID algorithm is simple to implement and has a wide range of adjustment, often allowing empirically acceptable performance to be achieved in spite of complex plant characteristics (Jaeger, 1986).

PID controllers are also the most commonly used controllers in industrial robots (Craig, 1986) which have many similarities to the skeletal systems in terms of the control needs. Like the motion in robots, the human body can be moved from an initial position (e.g. sitting) to a target position (e.g. standing) by forcing the joints to follow certain trajectories. In fact, this was easier said than done but many researchers have used the PID controller in FES systems. It was used either alone (Jaeger et al., 1989; Ewins et al., 1988; Fujita et al., 1990) or in combination with other controllers such a feedforward controller (Quintern et al., 1989) to control standing-up (Ewins et al., 1988; Quintern et al., 1989) and maintain standing (Jaeger et al., 1989; Fujita et al., 1990). The PID control used in this thesis is different in that it follows time-independent joint trajectories similar to those in Figure 1.2. Chapter 4 contains explanations on choosing these trajectories and the detailed control algorithms.

1.5.3 Switching Curve On/Off Control

Switching curve on/off control is a simple on/off control based on a switching curve that divides the state-space into regions of on and off actuator command. Such a control has been used to control standing-up and sitting-down (Andrews, 1990; Mulder et al., 1992a; Dolan et al., 1998). The primary objective was to control the terminations of the maneuvers, i.e., the KEV in standing-up and contact with the seat in sitting-down. The switching curve is a function defining the desired knee velocity versus the knee angle (Figure 1.2). During standing-up, in any given knee joint angular position, its actual velocity is compared to the desired velocity calculated from the switching curve. The stimulation to the knee extensors then is turned on if the actual velocity is lower than the desired velocity and turned off otherwise.

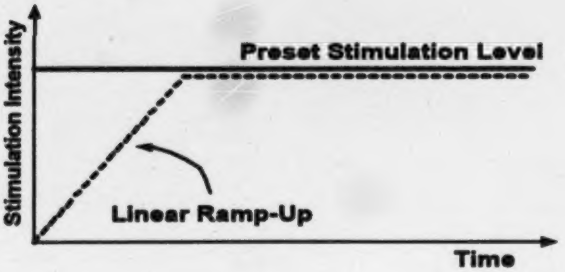
Stimulation Intensity
Preset Stimulation Level
Linear Ramp-Up
Time

Figure 1.1 Two variations of simple open-loop control of standing-up in paraplegia. Stimulation is delivered to the knee extensors.

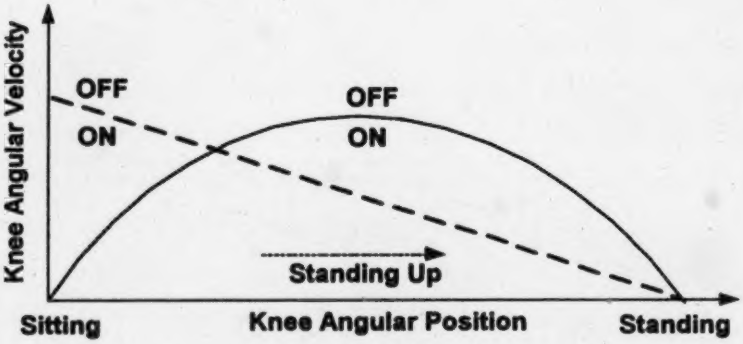
Knee Angular Velocity
OFF
ON
OFF
ON
Standing Up
Sitting
Knee Angular Position
Standing

Figure 1.2 Two switching curves for on/off control of standing-up. Both curves have zero KEV. ON and OFF represent the stimulation on/off regions.

1.5.4 Machine learning techniques

GA and RL are the two machine learning techniques used in this thesis to design FES controllers for standing-up. Both GA and RL however use ANN or FLC to store the learned information. The ANN and FLC, which are also the actual stimulation controllers, are nonlinear function approximators with many adjustable parameters. The optimal values of their parameters should be found by GA or RL based on the given optimization objectives.

Each one of these techniques has their own strengths and weaknesses. In this thesis, I combine them to form more powerful control techniques that are capable of handling the complexities involved in the control of FES-assisted standing-up in paraplegia. Almost all of these techniques have blossomed in recent years mainly because of the availability of the powerful digital computers. The number of research work on any of these techniques or hybrid systems that combine them is overwhelming. However, I am unaware of any study applying these techniques to the control of FES-assisted standing-up in paraplegia.

The following is a general introduction to these techniques and their origins without presenting mathematical formulas. More detailed explanation of the actual techniques employed in this thesis is given in the corresponding chapter.

1.5.4.1 Artificial Neural Networks

In 1943, a neurobiologist, Warren McCulloch, and a statistician, Walter Pitts, published a watershed paper (McCulloch and Pitts, 1943) that inspired to lunch the field of artificial neural networks by other researchers. This led to the invention of an element called perceptron by Frank Rosenblatt (Rosenblatt, 1959) which in turn sparked interest in neural computing. Since then, neural computing has made a substantial progress not only in theory but also in applications, aided by the increasingly powerful computers.

An ANN is a data processing system that attempts to achieve good performance via dense interconnections of simple computational elements. In this respect, ANN structure is based on our present understanding of biological nervous system. The high performance of the human brain in highly complex cognitive tasks was always a great motivation for modeling the brain. Hence, neural networks are often capable of doing things which humans or animals do well but which conventional computers often do poorly.

The building block of an ANN is a neuron. A neuron has many inputs and one or more outputs. Each neuron usually processes the inputs in two stages. It first calculates the weighted sum of the inputs and then passes the result through a transfer function before passing it to the output path. The inputs to a neuron might be the outputs of other neurons and its output path might be connected to another neuron's input. Each connection has its own corresponding weight. The signals on the input lines to a neuron are modified by these weights prior to being summed. An ANN consists of many interconnected neurons that are usually organized in layers. There are typically two layers with connection to the outside world. An input layer where data is presented to the network, and an output layer which holds the response of the network to a give input. The remaining layers are called hidden layers.

There are two main phases in the operation of an ANN, learning and recall. In most networks, these are distinct although in some cases they might be performed simultaneously. Learning is the process of adapting or modifying the connection weights so that the network outputs the desired values for the given input. When a knowledgeable teacher provides the network with examples of the desired output for a given input, the learning is called supervised learning. If no desired output is shown, the learning is called unsupervised learning. A third kind of learning, where an external teacher indicates only whether the response to an input is good or bad is called reinforcement learning. Recall refers to how the network processes the information provided to its input layer and generates a response at the output layer.

Unlike traditional expert systems where knowledge is made explicit in the form of rules, neural networks generate their own rules by learning from examples. This is especially more effective in complex tasks where it is difficult to articulate the rules.

An important characteristic of neural networks is the way they store information. The information is stored in distributed memory units, which are the connecting weights of the network. Consequently, the network responds reasonably even when presented with incomplete, noisy, or previously unseen input. The property is called generalization and considerably reduces the number of the examples required for learning. There are infinite numbers of input-output combinations for continuous variables and the network only needs to be trained with a limited number of input-output examples to work properly.

Instead of performing a program of instructions sequentially, neural net models explore many competing hypotheses simultaneously. Therefore, neural networks have great potential for parallelism, since the computations of the components are independent of each other. Neural networks, implemented in hardware, typically provide a greater degree of robustness or fault tolerance than sequential computers because there are many more processing nodes each with primarily local connections. Damage to a few nodes or links thus need not impair overall performance significantly. Because of fault tolerance or graceful degradation, neural networks are well suited for applications where failures can not be tolerated.

Neural networks are able to learn complex continuous mappings between the inputs and outputs. This ability is analogous to the ability of biological systems to learn coordinated movements. Therefore, it might be possible to build a neural network model to represent very complex nonlinear controllers necessary for the control of movement if a proper network structure can be found and a learning algorithm is available.

Most neural net algorithms adapt connection weights in time to improve performance based on current results. Therefore, a working model (or controller) may be found early in the learning and improved afterwards. When designing a neural network controller, it is not necessary to store all the information relevant to the system. The learning algorithm can store, in the neural network, only the information relevant to the control tasks. This is in contrast with the traditional control design method where, the detailed model of the system must be developed before designing the controller.

Thus the range of problems to which neural networks can be applied are those for which there is no precise model of any underlying process, or there is considerable noise, or there is considerable variation in the parameters of the problem or of its surroundings.

One disadvantage of the neural network models is the fact that it is not easy to understand why a fully trained neural network reaches a particular decision. For this reason, it is vital to tackle the problem of extracting knowledge from neural networks by the development of hybrid systems. Fuzzy logic controllers, described in the next section, have similar capabilities as the neural networks but the reasons for their decisions are visible to the user. They use a set of IF-THEN rules for decision making that are easily understood by the humans.

1.5.4.2 Fuzzy Logic Control

Fuzzy set theory was first introduced by Zadeh in 1965 (Zadeh, 1965). Since then, it has found many applications in a variety of fields. Among the most successful applications has been the area of fuzzy logic control initiated by the work of Mamdani and Assilian (Mamdani and Assilian, 1975).

A human operator may not always be able to properly control a process but can usually prescribe fairly good recipe for control. The recipe or control strategy may take the form of a set of rules relating the situations to actions known to the human operator. FLC's are rule-based systems that could model such a control strategy. Therefore, the FLC provides a framework to implement, in a digital computer, the human like approach to problem solving and control. Naturally, such a control is an efficient way to deal with imprecise and ill-defined data. FLC is particularly well suited to nonlinear and complex systems that would otherwise be difficult to model and control by conventional methods.

The operation of FLC has three stages (Figure 3.3): fuzzy encoding in fuzzification stage, Inference engine or control rule set, and fuzzy decoding in defuzzification stage. Fuzzy sets are used to label different regions of the input and output variables with linguistic variables such as "low", "medium" and "high". In fuzzification stage, crisp values of input variables are converted to membership values in the input fuzzy sets. Memberships of the output fuzzy sets are then found by executing all the rules relating the inputs to the outputs. Finally in defuzzification stage, the memberships of output fuzzy sets are converted to a crisp value as the controller output.

FLC can be designed by properly adjusting the control rules and the shape and number of the fuzzy sets. The rule sets can be extracted from an expert if s/he is able to directly articulate them. In this case the decision must be made on the shape and number of the fuzzy sets for each input and output variable. In the absence of an expert, the manual adjustment and trial-and-error approach can be used to tune the FLC. However, these methods fail when the system is complex and highly coupled or the number of variables are too high in which case, it is difficult to articulate in rules the relationship between the inputs and outputs. A number of techniques have been suggested to automate the parameter adjustment process in these cases. GA and RL are two of these techniques that will also be used in this thesis.

FLC has most of the advantages of the ANN and some more. They are capable of modeling complex nonlinear systems, can handle imprecise and noisy data and can generalize to unseen situations. Because of the way the state-space is divided by the fuzzy sets, they have better local representation than the ANN. FLC can be trained by both the supervised and unsupervised learning methods. Unlike the ANN which stores information in a manner that can not be interpreted by humans, the FLC stores the learned information in the set of rules that are easily understood by the humans. When using a learning algorithm such as GA or RL, the ANN must start with zero knowledge (random initial weights) and there is no way to incorporate the previous expert knowledge about the system. The initial FLC however, can incorporate the previous expert knowledge about the system very easily because both the FLC and the expert are speaking the same language. This initial FLC, although not optimal, provides a working and safe environment in which further learning can take place for optimal performance.

As we will see later, such a property is very useful in speeding-up the learning process and providing safety.

1.5.4.3 Genetic Algorithms

GA introduced by Holland (Holland, 1962) and subsequently studied by De Jong (De Jong, 1975) and Goldberg (Goldberg, 1989) among many others. GA was originally proposed as a general model of adaptive processes, but by far the largest application of the technique is in the domain of optimization (Back et al., 1997).

The basic concept of a genetic algorithm is to encode a potential solution to a problem as a series of parameters. A single set of parameter values is treated as the chromosome or genetic material of an individual solution. A large population of candidate solutions is created (initially with random parameter values). These solutions are essentially bred with each other for several simulated generations under the principle of survival of the fittest, meaning that the probability that an individual solution will pass on some of its parameter values to subsequent children is directly related to the fitness of individual (i.e. how good that solution is relative to the others in the population). Breeding takes place through use of operators such as crossover, which simulates basic biological cross-fertilization, and mutation (essentially the introduction of noise). This reproductive cycle continues until optimization of a fitness function.

In contrast to other optimization methods, GA only uses the value of the objective function and therefore, the function does not need to be continuous and differentiable. They can work with various types of variables at the same time as long as they can be encoded in a binary string. Instead of a single point, they simultaneously operate on a group of points within the search space. This increases efficiency in searching large spaces and robustness in finding global optimum of multi-modal functions. Therefore, GA can be applied to solving problems which are not yet fully characterized or too complex to allow full characterization, but for which some analytical evaluation is available. That is, problems for which we don't necessarily know how to make a good solution, but we can evaluate by some quantifiable measure the relative value of a solution (or at least the relative value of one potential solution in comparison to another).

GA and ANN are both inspired by computation in biological systems. A good deal of biological neural architecture is determined genetically. It is therefore natural to apply the evolutionary GA to determine the parameters of the ANN or in similar way the FLC.

GA has been used in conjunction with ANN or FLC in three ways. They have been used to set the parameters in a fixed architecture including both supervised and unsupervised learning applications. They have also been used to learn the topology or architecture of the FLC or ANN. This included the problem of specifying the number of hidden units, nodes and the way they should be connected in an ANN or the number of fuzzy sets and number of rules in a FLC. Finally they have been used to select training data for the ANN or FLC.

To synthesize controllers for paraplegic standing-up, I consider the musculoskeletal dynamics and the FES controller (FLC or ANN) as part of an overall optimization task in which the GA automatically tunes the controller's parameters.

1.5.4.4 Reinforcement Learning

Reinforcement learning is the problem faced by an agent that must learn behavior through trial-and-error interactions with a dynamic environment. RL has its roots in animal learning psychology and is based on the common sense notion that if an action is followed by a satisfactory outcome, then the tendency to produce that action should be strengthened i.e. reinforced.

RL includes a class of learning algorithms that build mappings from situations to actions to maximize a scalar reward signal. It does not rely on previous examples, teachers or models of the environment but learns only by its own trial-and-error interactions with the environment.

In contrast to supervised machine learning methods that once trained are thereafter static, RL does not require a set of a priori training examples representing the desired control actions. This is an advantage since the latter are often difficult or impracticable to obtain. Instead, RL requires only a scalar feedback or reinforcement such as a failure or success signal that is often easier to define a priori.

In the most interesting and challenging cases, actions may affect not only the immediate reward, but also the next situation, and consequently all subsequent rewards. Two characteristics, trial-and-error search and delayed reward are the two most important distinguishing features of RL algorithms.

Samuel's checkers playing program is probably the earliest program to use this idea (Samuel, 1959). Michie and Chambers (Michie and Chambers, 1968) used a reward-punishment strategy in their BOXES system, which learned to do cart-pole balancing. Inspired by Michie's work, Barto, Sutton and Anderson (Barto et al., 1983) used two neuronlike adaptive elements to solve the cart-pole balancing problem which in turn was the lunching pad for most of the RL research that followed.

RL is defined not by characterizing learning algorithms, but by characterizing a learning problem. Any algorithm that is well suited to solving the problem is considered an RL algorithm. There are two main strategies for solving RL problems. The first is to search in the space of behaviors in order to find one that performs well in the environment. This approach can be accomplished by the GA as described in the previous section. The second is to use statistical techniques and dynamic programming methods to estimate the utility of taking actions in states of the world. These techniques take advantage of the special structure of RL problems that is not available in optimization problems in general. This approach combines the fields of dynamic programming and supervised learning to yield powerful machine learning systems.

A RL agent generally consists of four basic components: a policy, a reward function, a value function, and a model of the environment. The policy is the decision making function of the agent, specifying what action it takes in each of the situations that it might encounter. This is the core of a reinforcement agent, because it alone is sufficient to define a full, behaving agent. The other components serve only to change and improve the policy. The reward function defines the goal of the reinforcement learning agent. It maps the state of the environment to a single number, a reward indicating the intrinsic desirability of the state. The agent's objective is to maximize the total reward it receives in the long run. The reward function thus defines what are the good and bad events for the agent. They are the immediate and defining features of the problem faced by the agent. As such, the reward function must necessarily be fixed. It may however, be used as a basis for changing the policy. For example, if an action selected by the policy is followed by low reward then the policy may be changed to select some other action in that situation in the future. Whereas the reward function indicates what is good in an immediate sense, the value function specifies what is good in the long run. Roughly speaking, the value of a state is the total amount of reward the agent can expect to accumulate over the future, starting from that state. Whereas rewards determine the immediate, intrinsic desirability of environmental states, values indicate the long term desirability of states after taking into account the states that are likely to follow, and the rewards available in those states. For example, a state might always yield a low immediate reward, but still have a high value because it is regularly followed by other states that yield high rewards, or the reverse could be true. To make a human analogy, rewards are like pleasure (if high) and pain (if low), whereas values correspond to a more refined and far sighted judgment of how pleased or displeased we are that our environment is in a particular state. Expressed this way, it is obvious that value functions formalize a very basic and familiar idea.

Rewards are in a sense primary, while values, as predictions of rewards, are secondary. Without rewards, there could be no values, and the only purpose of estimating values is to achieve more reward. Nevertheless, it is values with which we are most concerned when making and evaluating decisions. Action choices are made on the basis of value judgments. We seek actions that will bring about states of highest value, not highest reward, because these actions will obtain for us the greatest amount of reward over the long run. In decision-making and planning, the derived quantity called value is the one with which we are most concerned. Unfortunately, it is also much harder to determine value than it is to determine reward. Rewards are given directly by the environment, but values must be estimated and re-estimated from the sequences of observations an agent makes over its entire lifetime. One of the main things that reinforcement learning algorithms do is to efficiently estimate value, that is, to efficiently learn value functions.

The fourth and final major component of reinforcement learning agents is a model of the environment or external world. This is something that mimics the behavior of the environment. For example, given a situation and an action, the model might predict the resultant next state and next reward.

A form of RL algorithm extended to continuous state-space and multi-agent problems, is used in this thesis to design FLC stimulation controllers for FES assisted standing-up. The details of the algorithms are given in chapter 6.

1.6 Statement of Objectives

This thesis is involved with improving the design of FES controllers for standing-up in paraplegia. It is our objective to not use the detailed mathematical models of the musculoskeletal systems, as they are difficult to obtain. Therefore, the controllers are all model-free and there is no need for the accurate mathematical models to be developed. First, some of the open-loop and closed-loop controllers, used in the past by other researchers, will be evaluated to compare their merits and problems. This will provide us with a basis for comparison and will help us to identify the main problems associated with the control of standing-up. Finally, GA and RL will be used to design nonlinear ANN and FLC controllers to improve performance.

Although the controllers are all model-free, I will develop a simple model of standing-up to help us demonstrate the feasibility and effectiveness of the proposed control strategies. Therefore, the model of standing-up is only used as virtual patient to test the ideas and no knowledge of the model is used in designing the controllers. This will provide us with a safe and controlled environment to compare different strategies, evaluate their effectiveness and perform sensitivity analysis.

There are also two studies that are slightly off the main course of the thesis but are relevant to standing-up in paraplegia and its control. These include the development of a model of the voluntary arm forces during FES-assisted standing-up and generation of optimal joint trajectories for impaired standing-up.

Our specific objectives are summarized below:

1. The kinetic and kinematic data measured from the FES assisted standing-up in paraplegic patients will be used to develop a model of the voluntary arm forces. An ANN will be used as the model.

2. A computer model of standing-up in paraplegia will be developed and will be used as the virtual subject in design, development and comparison of the controllers. Realistic situations in the paraplegic standing-up will be modeled by including a model of the voluntary arm forces and assumption of the closed-chain dynamics.

3. Simple model-free control methods used in the past will be compared in terms of their performance to each other and to the FLC. Open-loop maximal stimulation of the knee extensors and three closed-loop methods including the switching curve on/off control, PID control and fuzzy logic control will be compared. Quantitative measures for robustness; total electrical stimulation, upper limb forces, terminal joint velocities and required design and implementation efforts will be used as basis for comparison.

4. A GA optimization method will be used to design nonlinear FES controllers for standing-up. A set of quantitative measures for total arm forces, total electrical stimulation, terminal joint velocities and scalar signals representing failure or success of the maneuver will be used to design the optimal controllers.

5. An RL algorithm will be used to design nonlinear FES controllers for standing-up. Similar optimality measures as (4) will be used to design the controllers.

6. A GA will be used to generate the optimal standing-up trajectories that are tailored to the needs and limitations of the people with impairments such as paraplegia and functionally impaired elderly.

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2 Neural Network Model Of The Voluntary Arm Forces During FES-Assisted Standing-up

2.1 Introduction

Functional Electrical Stimulation (FES) has been used for mobility restoration after spinal cord injury (Kralj and Bajd, 1989; Phillips, 1991; Graupe, 1994). The restored functions usually involve two fundamentally different kinds of controls; artificial FES control of the paralyzed extremities and the voluntary control of the intact muscles above the lesion. As an example, both of these controllers are important in a procedure commonly used for FES assisted standing-up where the subject's arms are used along with the electrical stimulation of the paralyzed lower extremity muscles (Figure 2.1).

The voluntarily controlled arms not only help to balance the body during the maneuver but also could carry as high as two-thirds of the body weight (Dolan et al., 1997; Kamnik et al., 1997). Therefore, the quality of the resulting motion depends strongly on how the arms musculature are controlled and if there is an appropriate coordination between the voluntary control of the arms and the artificial control of the lower extremity muscles. Such a coordination is essential because the independently designed artificial FES controller may conflict with the actions of the voluntary arm forces (Donaldson and Yu, 1996).

The importance of the voluntary control in FES assisted standing-up has been known for some time. In a study of FES control methods by Quintern et al. (Quintern et al., 1989), the lack of coordination between the natural voluntary and artificial FES control was recognized as an essential problem hindering the development of FES controllers. To provide such a coordination Donaldson and Yu (Donaldson and Yu, 1996) proposed a method for minimization of the arm forces. In their scheme, the arm forces should be measured and the leg muscles stimulated in a manner to unload the arms. In a three segmental model of standing-up, Veltink et al. (Veltink et al., 1995) simulated the activity of arms with forces in the shoulder joint. These forces were controlled by linear proportional integral derivative (PID) control laws with vertical velocity and horizontal position setpoints. However, no validation of the model was given. In our previous modeling studies (Davoodi and Andrews, 1996; Davoodi and Andrews, 1998a), we developed a qualitative model of the arm forces during standing-up motion using fuzzy logic controller. The controller was based on a set of general rules defined according to our observations and understandings of the motion objectives. For example, the rules of the fuzzy controller were defined so that the controller could keep the body's center of gravity inside the base of support and help lift the body when the upward progression velocity was less than a minimum. Although the model performance was very smooth and qualitatively comparable to the actual activity observed in paraplegics, it was general and not representative of an individual subject's voluntary control actions. To work properly, the FES controller must be coordinated to the voluntary control of each individual, which might be significantly different from the others. Electromyographic (EMG) activity of the muscles in the supporting arm during standing in paraplegia (quiet standing and one arm raise) has revealed consistent sequence of muscle activity for a given subject, but showed variability from person-to-person (Moynahan, 1995). They called this 'personal strategies' for postural control. We hypothesize that similar 'personal strategies' exist for the control of arms during FES assisted standing-up and that these strategies can be cloned with nonlinear neural network models.

In the past, two main obstacles have hindered the integration of artificial and voluntary control in FES systems. First, it was difficult to mathematically characterize the voluntary control behavior with acceptable accuracy. Second, the conventional control theory did not have the necessary tools to deal with systems as complex as the voluntary control. Here, we investigate the first problem and show that the accurate models of the voluntary control strategy during the FES assisted standing-up can be developed. We use neural networks to develop models of the voluntary arm forces in individuals using the data measured from them during the repeated standing-up trials. We then discuss how these models might be used to design FES controllers that are coordinated to the voluntary controllers. Sit-to-stand maneuver was chosen because it is a prerequisite for many of the daily life activities such as walking and reaching for objects not accessible from the wheelchair. Furthermore, the voluntary arm forces are integral part of the maneuver and contribute considerably to the quality of the resulting motion.

Researchers from different fields have shown interest in modeling human behavior in Man-Machine systems. Early models during the World War II were developed to improve the performance of the pilots, gunners and bombardiers in the human-in-the-loop systems (Hess, 1996). They were linear and inherently incapable of modeling nonlinear aspects of the human control behavior. Optimal control models were based on the assumption that the human operator seeks to optimize some objective function of the task at hand (Kleinman et al., 1970; Winters, 1997). Models based on the actual input-output data of the human, measured during the control of an actual or simulated process ranged from parametric system identification procedures (Cooper, 1991) to nonlinear expert systems based on Rule-Based systems (Michie et al., 1990; Popovic et al., 1997), Fuzzy Logic models (Dillmann et al., 1995; Kramer, 1985; Liu and Wu, 1993) and Neural Network models (Enab, 1995).

2.2 The Modeling Task

Figure 2.1 shows a planar model of a popular method for FES assisted standing-up. The strategy, introduced first by Bajd et al. (Bajd et al., 1981), uses both the arms and the electrical stimulation of the knee extensors for standing-up.

In this model, the sit-to-stand maneuver is viewed as a task in which the positions of the three segments including the shank, thigh and trunk must be coordinated to move the subject from sitting to standing position. The three segmental system is affected by two actuators. FES actuators position the knee joint and the arms are viewed as the actuators that by applying the forces and moments position the shoulder joint and trunk to help in sit-to stand maneuver. The modeling task is to identify this actuation strategy, i.e., to find a model that for the given state of the three segmental system could produce the shoulder forces similar to those observed in the experiments. Therefore, the model will replace the two blocks above the dashed line in Figure 2.1.

To develop such a model, we need to identify the necessary inputs to the model. The actual decision making process employs sensory information from vestibular, visual, proprioceptive, and exteroceptive systems (Kandel et al., 1991) which are not available for direct measurement. Therefore, we decided to use a different set of measurable variables that could partially, but sufficiently for the task at hand, replace the sensory information accessed by the central nervous system. The state information of the three segmental system defined by the angular positions and angular velocities of the ankle, knee and hip joints were used to resemble the information received from the visual and vestibular systems. The forces and moments in the shoulder joint (which are correlated to the forces in the arms musculature and the hand contact forces) were used to resemble the proprioceptive and exteroceptive information from the intact upper extremities.

2.3 Experimental Procedures

2.3.1 Subjects

Eight paraplegic patients participated in the study, five men and three women. Their ages ranged from 17 to 57 years, weights from 58 to 95 kilograms and heights from 159 to 185 cm. Sample group included patients with different levels of spinal cord injury and different experiences of FES usage as summarized in Table 2.1.

2.3.2 Instrumentation

The measuring system used in the analysis consisted of two measuring frames, which were built as copies of a wheelchair seat and conventional walker. The seating frame was instrumented by the use of AMTI force plate providing information of the seat support forces, while the forces on the arm support frame were assessed by the six axis JR3 robot wrist sensor. Additional AMTI force plate was used for measuring the ground reaction forces under a foot. Kinematics of the body movement was assessed by the OPTOTRAK contact-less optical system measuring the 3D active markers position. The markers were attached to the ankle, knee, hip, pelvis, shoulder, elbow, wrist, and head. Because of the symmetry assumption about the sagittal plane, all parameters were recorded only for the right side and calculated for the left side.

2.3.3 Protocol

Subjects were seated on the instrumented seat with the arms resting on the arm support frame. The height of the seat coincided with the height of a wheel chair, while the arm support frame height was adjusted according to the patient's preferences. The feet were positioned in such a way that the right foot was placed flat on the force plate. After approximately two seconds from starting the data collection, the subject was asked to stand up. The subjects were asked to rise in their preferable way and speed, while using stimulation of knee extensors and arm support. At least five rising trials were recorded for each participant with the 50 Hz sample rate, each trial lasting for 10 seconds.

2.3.4 Data analysis

The signals collected from active markers, force plates and wrist sensor were interpolated and filtered by the 4th order Butterworth filter with 5 Hz cut-off frequency. The coordinate systems of all sensors were transformed to coincide with the reference coordinate system placed on the floor in the center of the arm frame. Since the human body symmetry was presumed, all parameters were gathered only for the patient's right side and calculated for the left side.

The training data for the model consists of angular positions and angular velocities of the ankle, knee and hip joints and the forces and moments at the shoulder joint. The kinematics of the markers and anthropometric data were used to calculate the angular positions of the joints, kinematics of the joint centers, and segmental mass centers. Velocities and accelerations were calculated by differentiating the positional data. The kinematics of the arms and the force measurements of the arm support were fed to an inverse dynamic model of the arms to calculate the forces and moments at the shoulder joint.

2.4 The Proposed Neural Network Model

2.4.1 Topology of the neural network model

The basic structure of the model is a three-layered fully connected feedforward neural network as depicted in Figure 2.2. To further enhance this nonlinear function approximator (Hornik et al., 1989), the past inputs and outputs are fed to the input layer to provide the network with the memory required in modeling the dynamic systems. These delayed signals have been shown to improve performance when applied to recognition of time series such as speech signal (Lang et al., 1990).

2.4.2 Selection of the input variables

We used the visual inspection of the input-output scatter plots and a nonlinear correlation method to identify the most important input variables. The nonlinear correlation technique was based on the nonlinear neural networks. A moderate size neural network was trained to represent the relationship between one of the inputs and one of the outputs. The root mean square error (RMSE) between the actual output and the model predicted output was calculated as an indication of how strongly the output is correlated to the input. The smaller the RMSE the stronger the correlation. The size of the network was kept constant to make sure that the comparison is valid. The Neural Network Toolbox (The Mathworks Inc., USA) was used to train these neural networks.

2.4.3 Neural network training method

The neural network models were trained using the Neuralwork Predict (NeuralWare Inc., USA). It uses a cascade method of network construction together with an adaptive gradient learning rule to train the network. In the cascade method of network construction method, training begins with zero hidden layer nodes and new hidden layer nodes are added one at a time with the purpose of predicting the current remaining output error. The process of adding the hidden layer nodes continues until no improvements can be made. The details of the training procedure can be found in (NeuralWare, 1993).

2.5 Results

2.5.1 Selection of the input variable

There was strong nonlinear correlation to the present samples of the angular position inputs $\theta_1(t),\theta_2(t)$ and $\theta_3(t)$ and strong linear correlation to the most recent samples of the outputs F_Z (t-1), F_Y (t-1) and M_X (t-1). Therefore, these variables were selected as the inputs to the model.

Compared to the selected variables, the correlation to the angular velocities and other delayed samples were weaker and therefore were excluded from the model. The correlation to the angular position had also peaks at samples 280-400 ms and 700 ms in the past. These variables however were not included in the model because they increased the memory required to store the old samples and they had negligible effect in improving the model accuracy.

2.5.2 Model trained for subjects MT

A neural network model was successfully built to predict the voluntary arm forces (F_Z, F_Y and M_X) of subject MT during standing-up. The model predictions are compared to the measured values in Figure 2.3. The model performs well not only on the training data but also on the validation data never used in the training process. The validation data constitutes the last 20% of the presented data. Figure 2.5 and Table 2.2 represent the consistency of the adopted voluntary control strategy by MT. The consistency is quantified by statistical measures such as RMSE, confidence interval and correlation of the model predictions to the measured behavior. Lower values of RMSE and confidence interval and higher value of correlation show that the voluntary control strategy represented by the model has better consistency and therefore less corrective and unpredictable behavior.

2.5.3 Model trained for the rest of the subjects

The performance of the models trained for MK (least experienced), TM (youngest with the highest level lesion), SB (lowest level lesion), BJ (tallest and heaviest), ZJ (lightest and oldest) and MT (most experienced) are summarized in Figure 2.5 and Table 2.2.

2.5.4 Comparing the voluntary control strategies

Models developed for individual subjects were evaluated on test data consisting of eight sample standing-up trials. Each one of the eight trials belonged to one of the subjects and had never been used in training. The objective was to investigate the similarities and differences in the voluntary control strategies adopted by the subjects.

Figure 2.4 shows how the voluntary control of MT compares to the other subjects. Here the measured values of other subjects were input to the model of MT and the predictions of forces and moments were compared to their actually measured values. This is equivalent to asking the other subjects to use the control strategy of subject MT to control their arms. Similar procedure was applied to models of the other subjects with the statistical measures of prediction performance given in Figure 2.6 and Table 2.3. The subject's control strategy is more similar to the collective behavior of the group of eight paraplegics when the value of RMSE or confidence interval are lower or the correlation value is higher.

2.6 Discussion

Since the system is highly nonlinear, a nonlinear correlation analysis was devised and successfully used to identify the relevant input variables.

There was strong correlation to the angular position of the joints than the angular velocity that may suggest the voluntary arm forces during standing-up is primarily position dependent. Lower correlation to angular velocities might be due to the fact that FES assisted standing-up in paraplegia is relatively slow. Also strong correlation to the past samples of the arm forces shows that the proprioceptive feedback plays an important role in the voluntary control of the arm forces. In addition to high correlation of the model outputs to most recent inputs, there were also correlation peaks to inputs delayed by 280-400 ms and 700 ms that may suggest there are short and long delay control loops involved in this postural adjustment task (Jaeger, 1986).

The neural network model developed for MT performed well on both the training and the validation data. Therefore, it is possible to accurately model the voluntary arm forces during standing-up. The good performance on the validation data shows that the model has generalized well and that the subject's control strategy is consistent from trial to trial. Therefore, subject MT has developed a unique control strategy for the use of her arms and uses it consistently. This verifies the development of the 'personal strategy' by the paraplegics to control their arms during standing-up which is compatible with the observations made by Moynahan (Moynahan, 1995) in paraplegics during standing.

Similar models were successfully developed for the other subjects, all of them showing consistency in performing the learned 'personal strategy'. However, the consistencies were not the same. The adopted control strategy and consistency in performing it depended on parameters such as experience of FES use, level of injury, weight, height and age of the subject. Comparing the data in Figure 2.5 and Table 2.2 shows that subject MT who was the most experienced FES user (has been in the program longer), had the highest consistency. This is evident from the very low confidence interval, lower absolute errors and lower RMSE. The highest inconsistency belonged to TM who had the highest level lesion (T3-4). This is in contrast with her long history of FES use as shown in Table 2.1. The insufficient control over the trunk muscles due to the high level lesion most probably prevents her from effectively stabilizing her trunk. The unstable trunk could disturb the maneuver and therefore require more corrective actions from the arms that in turn results in less consistent control strategy.

Comparison of the control strategy adopted by MT to that of the others in Figure 2.4, shows more similarity to some subjects than the others. However, it shares a general trend with all of the subjects. This is an expected result because during standing-up motion, the arms must play a similar role, i.e., provide balance and help in rising. Therefore, there may be general rules that govern the control of the arm forces in all of the subjects. This is compatible with our previous study (Davoodi and Andrews, 1998a), where we developed the rules of a fuzzy control model of the arm forces based on our understanding that the arms try to keep the center of mass inside the foot support area and maintain a minimum upward velocity. The results in this study only suggest that there are general rules applicable to all of the subjects but it is not clear whether our understanding of these rules in (Davoodi and Andrews, 1998a) were correct. This needs further study. On the other hand, there are control rules that are specific to the individual subjects, which is apparent from the incompatibilities shown in Figure 2.4. The control strategy adopted by MT had striking similarities with MK and SB but differed in some aspects with the others. Therefore, there are person-to-person differences in the adopted arm force control strategies in standing-up which is compatible with the observations of Moynahan (Moynahan, 1995) for the case of standing in paraplegia. As shown in Figure 2.3, most of the differences are in the control of M_X which is responsible for the control of trunk orientation. The ability to control the orientation of the trunk depends on factors such as the lesion level, which is different among the subjects. Therefore, the control of trunk orientation shows more variability among the subjects.

Table 2.3 and Figure 2.6 show the similarity of each subject's control strategy to the collective behavior of the group. Here again MT, as the most experienced subject, behaves closer to the average behavior of the population of eight paraplegics. The confidence interval and the RMSE are the lowest in most cases and the correlation value is higher. TM on the other hand has the highest dissimilarity which is again attributable to her high lesion level that forces her to adopt a control strategy that is not only more variant but also different from the others.

The results in this study shows the possibility of developing neural network models capable of cloning the personal strategies of paraplegics to control their arms during standing-up. Such individualized models can potentially be used to tailor the FES controllers to the needs of the individual subjects. The model of the voluntary arm forces can be combined with the musculoskeletal models of the lower extremities (which are relatively easier to model) to develop a realistic cybernetic model of a paraplegic subject. This model can then be used with a learning procedure such as the reinforcement learning (Davoodi and Andrews, 1998a) or genetic algorithms (Davoodi and Andrews, 1998) to develop optimal FES controllers. The individualized models can also be used in the procedure described by Donaldson and Yu (Donaldson and Yu, 1996) where the sensors are necessary to measure the arm forces which is then used to adjust the stimulation of the leg muscles. An individualized neural network model will have the prediction capability, which could make all the difference. Because, instead of measuring the arm force and adjusting the electrical stimulation accordingly (which will be late because of the considerable neurotransmission delay), the models can help to predict ahead the arm forces and adjust the stimulation in advance.

Finally, the models of the voluntary control strategy have potential application in a variety of areas such as the analysis of human control, design of unmanned vehicles, human-machine interfacing, real-time training, development of human-like intelligent machines, human-robot coordination and the transfer of skill from one human to another (Nechyba and Xu, 1997).

2.7 Conclusions

Accurate neural network models of the voluntary arm forces during FES assisted standing-up in paraplegia were developed. The models performed well both in training and validation data and therefore were able to generalize to the unseen situations.

Each subject develops his/her own personal strategy and executes it consistently. The consistency is dependent on the factors such as the experience in the use of FES, the level of injury, and other subject-specific parameters. Each subject's personal strategy has substantial similarities to that of the other subjects. This might be due to the similarities in the objectives of the arms in standing-up. There are also subject specific properties that are responsible for inter-subject differences. Inter-subject variations were higher in the control of the trunk orientation, which is performed by the shoulder moment. The voluntary control of the most experienced subject was not only most consistent but also closer to the average behavior of the population of eight paraplegics.

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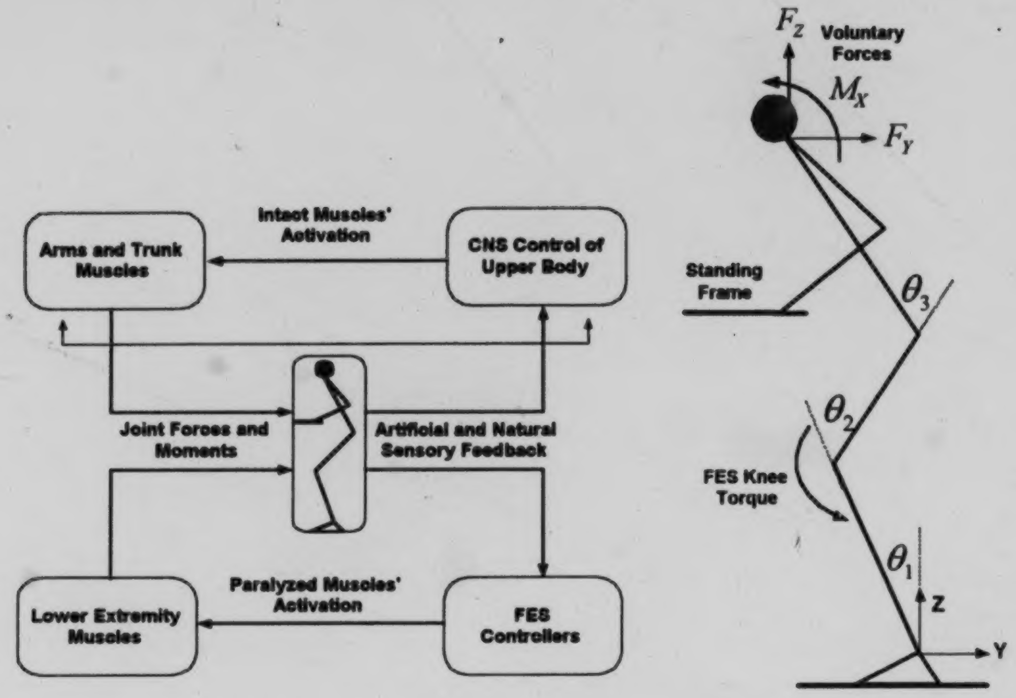
Intact Muscles' Activation
Arms and Trunk Muscles
CNS Control of Upper Body
Joint Forces and Moments
Artificial and Natural Sensory Feedback
Paralyzed Muscles' Activation
Lower Extremity Muscles
FES Controllers
F_Z
Voluntary Forces
M_X
F_Y
Standing Frame
θ_3
θ_2
FES Knee Torque
θ_1
Z
Y

Figure 2.1 Artificial and natural control in FES assisted standing-up in paraplegia. A sagittal view of the subject is shown on the right. In addition to electrical stimulation of the knee joint extensors, the voluntary arm forces help in lifting the body and keeping the balance. The equivalent forces and moments at the shoulder joint F_Y, F_Z and M_X represent the overall force actions of the arms' musculature at the shoulder joint. Dashed lines represent the reference line for measuring the ankle, knee and hip joints. Two control loops affecting the FES standing-up in paraplegia are shown on the left.

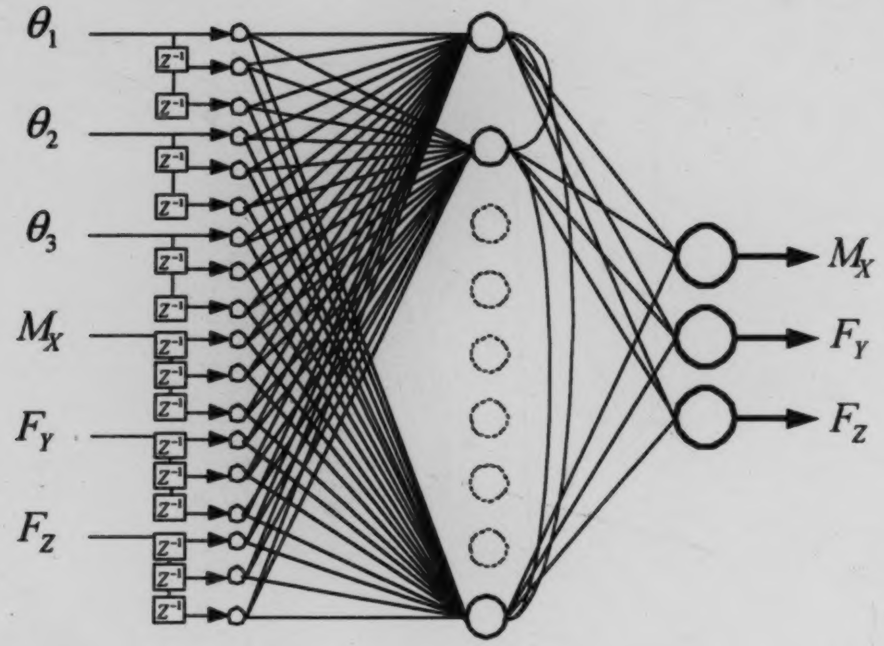

Figure 2.2 Topology of the neural network model of the voluntary arm forces. Present and past state information plus the past samples of the outputs form the inputs to the model (angular velocity inputs are not shown for clarity). The outputs are the forces and moment at the shoulder joint. Hidden layer is fully connected to the input and output layer. Each hidden node receives connections from previously established hidden nodes (hidden nodes are added one at a time by the training procedure).

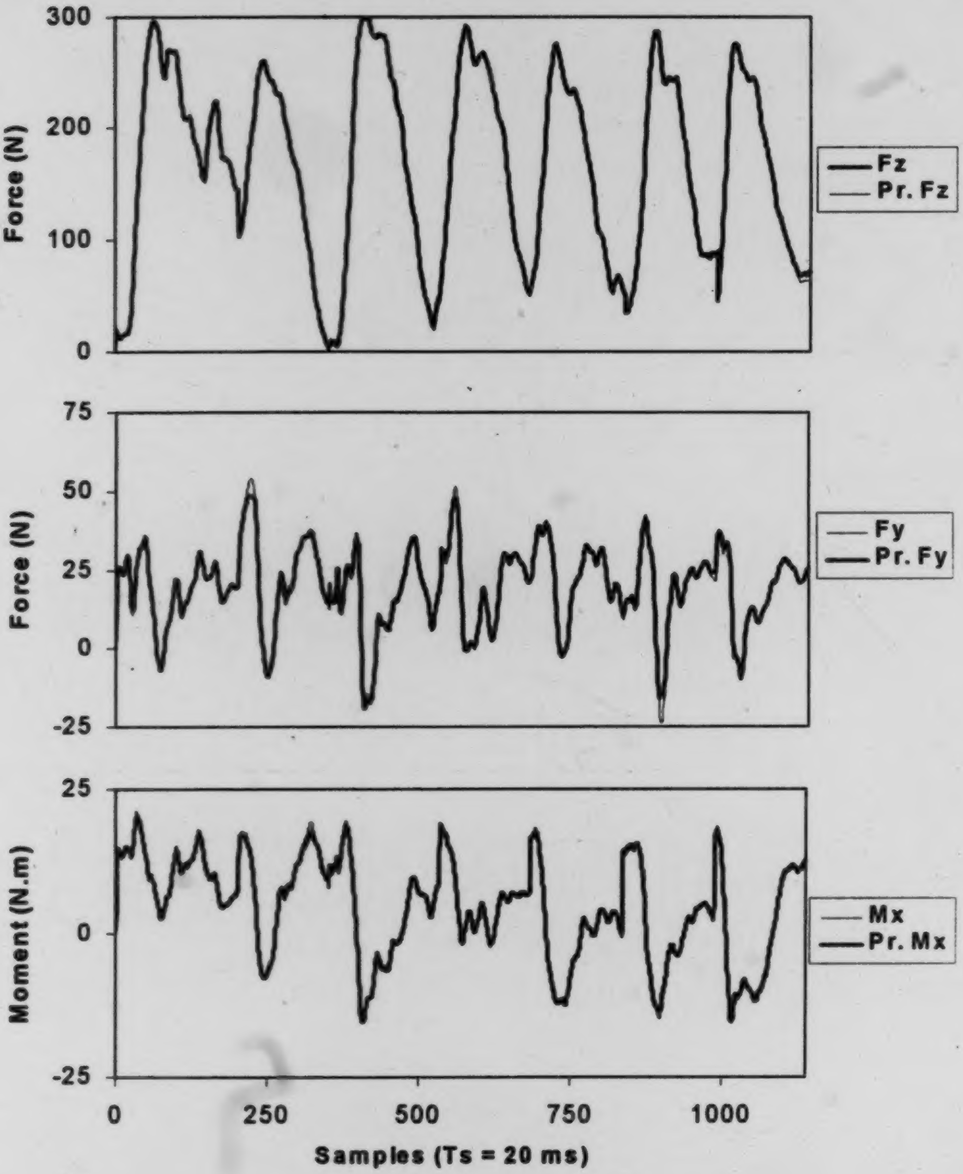

Figure 2.3 Predictions of the neural network model for subject MT. Predicted forces and moment (Pr. F_Y, Pr. F_Z and Pr. M_X) are compared to the measured arm forces F_Y, F_Z and M_X.

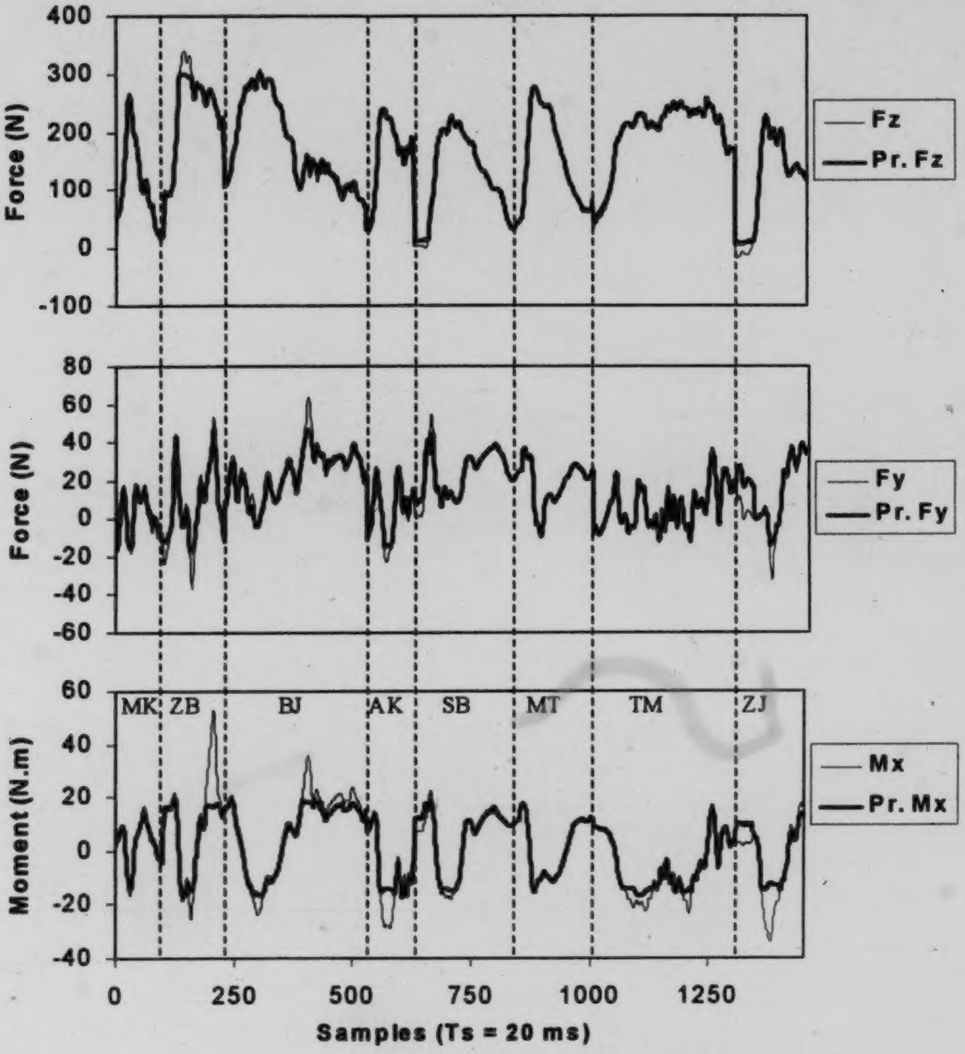

Figure 2.4 Predictions of the model of MT on the data collected from other subjects. Pr. F_Y, Pr. F_Z and Pr. M_X are the predictions of MT's model when fed with the inputs from other subjects' measurements. F_Y, F_Z and M_X are the arm forces measured from all of the subjects. The portions of the data between the dashed lines belong to one subject as indicated in the figure.

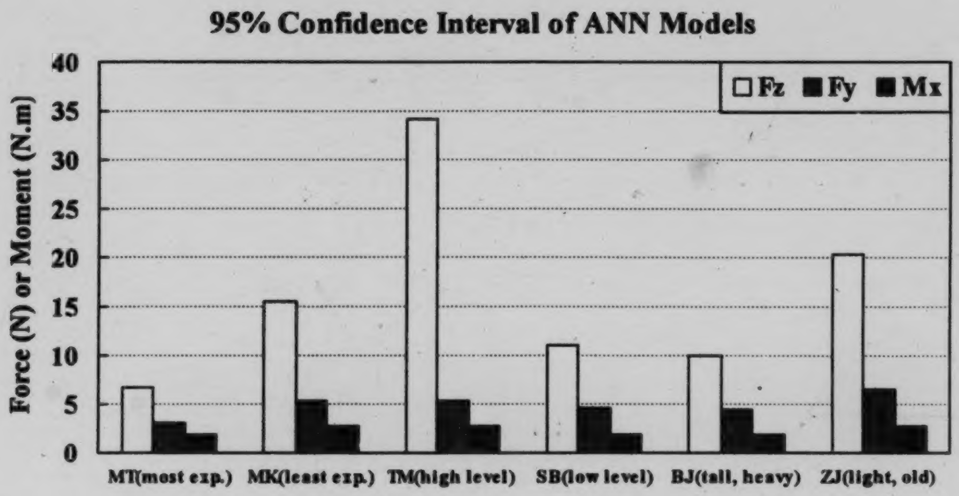

Figure 2.5 Confidence interval of the neural network models. The model predictions are compared to the measured data of the same subject in repeated trials (last column of Table 2.2). Lower value of the confidence interval means better consistency and therefore less corrective and unpredictable behavior.

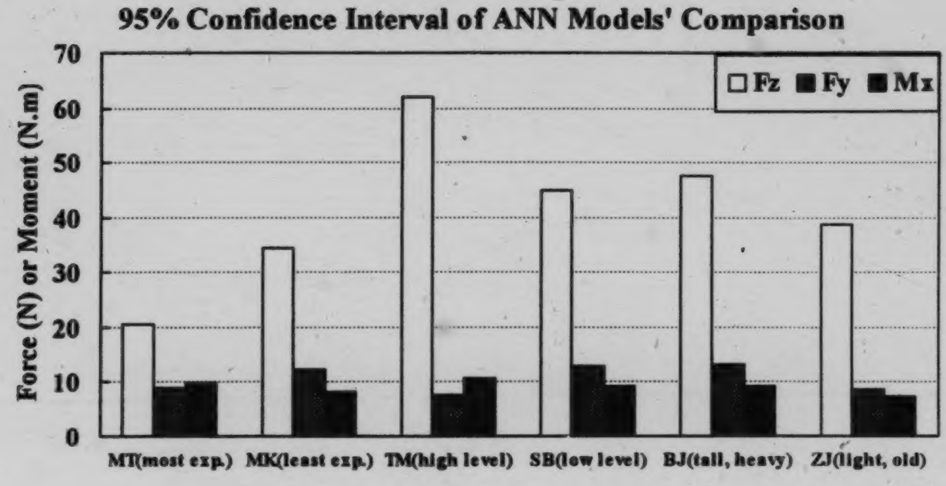

Figure 2.6 Confidence interval of the neural network models. The model predictions are compared to the collective behavior of the group (last column of Table 2.3). This is equivalent to asking all the subjects to use the voluntary control of one subject and then evaluate how close that subject's behavior is to the average behavior of all the subjects. Lower value of the confidence interval means better consistency and therefore less corrective and unpredictable behavior.

	MK	ZB	BJ	AK	SB	MT	TM	ZJ	Mean
Sex (M/F)	M	M	M	M	M	F	F	F	-
Age (years)	23	22	23	44	31	28	19	57	32.0
Weight (kg)	58	74	85	74	64	75	59	53	70.3
Height (cm)	168	184	185	180	183	171	178	159	79.3
Injury Level	T9	T10-11	T9	T10-11	T10-12	T4-5	T3-4	T11	-
FES Use (months)	2.5	6	5	6	11	60	42	36	21.1

Table 2.1 Paraplegic subjects who participated in the study.

		R	RMSE	AAE	MAE	CI (95%)
MT	F_Z	0.999	3.425	2.297	44.752	6.666
	F_Y	0.992	1.614	1.105	11.867	3.141
	M_X	0.994	0.982	0.577	12.083	1.911
MK	F_Z	0.993	7.959	4.508	93.066	15.500
	F_Y	0.974	2.801	1.758	24.243	5.456
	M_X	0.984	1.447	0.865	13.030	2.819
TM	F_Z	0.977	17.560	7.291	236.709	34.151
	F_Y	0.980	2.782	1.690	37.570	5.411
	M_X	0.995	1.404	0.912	20.720	2.731
SB	F_Z	0.997	5.667	3.947	55.315	11.025
	F_Y	0.981	2.436	1.627	25.939	4.740
	M_X	0.994	1.012	0.633	12.162	1.970
BJ	F_Z	0.997	5.105	3.153	61.782	9.934
	F_Y	0.983	2.342	1.512	21.919	4.557
	M_X	0.997	1.020	0.648	9.617	1.986
ZJ	F_Z	0.992	10.443	5.256	141.434	20.321
	F_Y	0.984	3.326	2.172	35.732	6.472
	M_X	0.995	1.401	0.876	12.633	2.727

Table 2.2 Statistics comparing the model predictions to measured data in individuals. Correlation (R), root mean square error (RMSE), average absolute error (AAE), Maximum absolute error (MAE) and 95% confidence interval (CI) are given.

		R	RMSE	AAE	MAE	CI (95%)
MT	F_Z	0.992	10.549	5.299	177.588	20.526
	F_Y	0.960	4.610	2.837	31.223	8.971
	M_X	0.947	5.053	2.846	36.561	9.831
MK	F_Z	0.978	17.645	10.531	133.418	34.333
	F_Y	0.930	6.269	3.775	35.680	12.198
	M_X	0.961	4.240	2.436	31.821	8.251
TM	F_Z	0.924	31.834	21.027	143.503	61.942
	F_Y	0.969	4.004	3.014	31.973	7.792
	M_X	0.953	5.480	3.164	42.685	10.663
SB	F_Z	0.964	23.023	14.757	130.741	44.798
	F_Y	0.925	6.638	4.496	33.407	12.917
	M_X	0.947	4.772	2.812	33.738	9.286
BJ	F_Z	0.955	24.385	12.907	191.774	47.447
	F_Y	0.944	6.852	4.059	41.321	13.334
	M_X	0.951	4.656	2.623	23.810	9.060
ZJ	F_Z	0.977	19.885	13.296	172.180	38.690
	F_Y	0.971	4.345	3.170	38.666	8.456
	M_X	0.966	3.749	1.773	34.336	7.295

Table 2.3 Statistics comparing the model predictions to measured data in the group. Correlation (R), root mean square error (RMSE), average absolute error (AAE), Maximum absolute error (MAE) and 95% confidence interval (CI) are given.

3 Cybernetic Model of FES-Assisted Standing-up

3.1 Introduction

3.1.1 Standing-up using FES after spinal injury

Functional Electrical Stimulation (FES) has been shown to be clinically feasible for standing-up (Bajd et al., 1982; Petrofsky et al., 1984; Marsolais and Kobetic, 1987; Andrews et al., 1988). Standing-up is important because it is a prerequisite for many activities of daily life such as transfers and is a precursor to reaching objects and ambulation. In addition, there may also be some therapeutic and psychological benefits with regular upright weight bearing (Andrews and Wheeler, 1995).

Currently, FES assisted standing-up is performed by activation of the knee joint extensors with a preset constant level stimulation delivered in an open-loop manner (Bajd et al., 1982). In practice, the intensity of the constant stimulus is usually adjusted to reach a compromise between reducing the KEV and the amount of upper limb effort required to lift-off the seat. There are however factors that limit patients ability to perform sit-stand-sit maneuvers with open loop FES. For example, some patients may not tolerate well the stimulus sensation with surface electrodes or may have upper limb impairment or be overweight. In addition, as spinal injury survivors age, their chances of losing independence increase due to arm injuries and pain. The long-term effects of transfers and wheeling are often reported as causing or exacerbating arm injury and pain (Chisholm, 1997). High terminal knee velocities may also be a concern since it is not known if such repetitive insults to the ligaments may ultimately lead to damage, as it is the ligaments that absorb all the energy in bringing the leg to a rapid and jerky halt.

The motivation for the present study is that there appears to be potential for improvement using feedback control techniques in which the stimulus parameters are automatically adjusted throughout the maneuver.

3.1.2 Modeling FES standing-up in paraplegia

Mathematical models, when validated, can provide a safe and convenient test-bed environment with precisely controllable experimental conditions for the design and evaluation of controllers prior to human trials. They can be used to predict the response of a paraplegic when subjected to controlled disturbances for different FES control schemes. Stability and behavior of the system under various conditions, and sensitivity to variations in the model and control system parameters can also be investigated. Repeated trials are straightforward and similar experiments can be repeated using different control schemes before proceeding to clinical trials. However, the development of a mathematical model for the musculoskeletal system is nontrivial and many simplifications are required to keep the modeling task tractable.

Mathematical models of FES standing have been developed with various degrees of complexity. Jaeger (Jaeger, 1986) reported a three segmental static model and a single link dynamic model that were used to study the restoration of quiet standing by FES control of the ankle joint motion. The motion was controlled in the close vicinity of the vertical standing posture and there were no upper limb interactions. Khang et. al. (Khang and Zajac, 1989a; Khang and Zajac, 1989b) modeled the standing-up motion by a planar four segment system (i.e. foot, shank, thigh and trunk-head). The feet were assumed to be flat during the motion and upper extremity force actions were treated as external disturbances and replaced by horizontal force, vertical force and a moment acting at the shoulder. Veltink (Veltink et al., 1995) proposed a three segmental model of standing-up in which the arm forces were modeled by linear proportional control laws with vertical velocity and horizontal position setpoints.

3.1.3 Closed-form configuration of the link model

FES standing-up in paraplegics involves the upper limbs in which the body segments form a closed chain between the hands and the feet i.e. a closed-form dynamical system. The closed-form configuration shows special dynamic behaviors that are absent in the open-form configuration used in previous studies. For example, the shoulder trajectory is constrained by the geometry of the segmental links and the inter-segmental dynamic couplings are more significant. The previous reports have not accounted for the fact that FES assisted standing in paraplegia has a closed-form configuration. Voluntary arm forces are quite essential as they may carry up to two-thirds of the body weight in some instances of open loop FES standing-up (Dolan, 1997; Kamnik et al., 1997). These forces have two primary objectives, providing balance by applying horizontal forces and compensating for the deficiencies in joint torques by applying upward forces to support body weight. The arms do not merely impose random disturbances, they are the output of the intact CNS that reflects the integrated output of the intact upper trunk, arms, and head neuromuscular sub-systems. They provide significant and precisely controlled force actions as a learned skill that is both self-adaptive and anticipatory (Moynahan, 1995) based on the intact senses including vision, the vestibular system, proprioception and exteroception. The arm force actions are based on learned skills that anticipate the actions of the FES machine so as to optimize control in the presence of external disturbances and internal changes and disturbances such as muscle fatigue and reflex actions. This is a cybernetic man-machine system in which skill learning occurs. In the case of fixed parameter FES controllers only human learning occurs. In adaptive FES controllers based on machine learning there is, in principle, the possibility for mutual learning between man and machine but such systems have not yet been studied and it is hoped that such learning will be cooperative.

In the human, the upper limbs and shoulder girdle are ill adapted for locomotion and weight bearing. It is often the stated objective of FES control to minimize their involvement particularly vertical force actions associated with body weight support. The reasons for reducing upper limb forces have been indicated above, for example to reduce the risk of various overuse injuries, however the risks have not been systematically studied and there are no guidelines as to the desirable limits on arm force actions. The fact remains that with the present state of the art, and probably for the foreseeable future, the upper limbs will play an unnatural but essential and probably predominant role in FES assisted locomotion. The high values of the voluntary forces and the fact that they are controlled intelligently requires a more realistic treatment. Here we will make the assumption that the upper limbs are working cooperatively with the FES subsystem as a Man-Machine system and that the whole system mechanically forms a closed chain.

3.1.4 Man-Machine Models involving arm force actions

Researchers from different fields have been interested in modeling human behavior in Man-Machine systems. Engineers were interested in improving the performance of the human-in-the-loop systems and designing controllers for complex systems by imitating the human experts. Neuroscientists on the other hand were interested in principles underlying the human control behavior.

Early models during the World War II were developed to improve the performance of the pilots, gunners and bombardiers in the human-in-the-loop systems (Hess, 1996). The human was considered as an inanimate servomechanism with a well-defined input and output. These models were adequate for some engineering applications but were limited in terms of the number of inputs and outputs and the complexity of the controlled systems. They were also linear and inherently incapable of modeling nonlinear aspects of the human control behavior. Optimal control models are based on the assumption that the human operator seeks to optimize some objective function of the task at hand (Kleinman et al., 1970; Winters, 1997). Optimal models may help us to understand reasons behind certain patterns of movements but many of the daily life movements may be personally satisfying as opposed to being optimal (Hogan and Winters, 1990). Further, it is not clear, how the optimization criteria and the relative weighting of the subcriteria for the tasks should be identified. Models with various level of sophistication were developed using the actual input-output data of the human, measured during the control of an actual or simulated process. The methods ranged from parametric system identification procedures (Cooper, 1991) to nonlinear expert systems based on Neural Networks (Enab, 1995), Rule-Based systems (Michie et al., 1990; Popovic et al., 1997) and Fuzzy Logic models (Kramer, 1985; Liu and Wu, 1993; Dillmann et al., 1995). Linear system identification models are not suitable for the inherently nonlinear human control (Cooper, 1991). Their structure must be identified a priori and they are difficult to apply to the multi-input multi-output (MIMO) systems. A Neural Network used by Enab (Enab, 1995) to model the human operator of a chemical process, was claimed to have better generalization to the other tasks than the conventional linear models. In 1960 Peter Donaldson originated a technique he called error decorrelation to automatically extract the input-output control relationships used in learned behaviors such as balancing a pole (Donaldson, 1960). Donald Michie further extended the technique using a rule induction machine learning algorithm to automatically extract the control rule-sets of a human controlling the computer simulation of the cart-pole system. This technique is now referred to as "Behavioral Cloning" and has the clear advantage of being able to automatically determine rules describing human skill in a form suitable to implement in an computer based expert system. This contrasts with the alternative knowledge engineering techniques that rely on the subjects ability to articulate these rules, an almost impossible task if the behavior is performed subconsciously. The technique was first applied to the control of a FES system similar to that described by Kralj & Bajd in (Kralj and Bajd, 1989) by cloning the learned skill of a spinal injured patient manually operating a crutch hand-grip mounted momentary-action switch to alternate between the extension and reflex flexion phases of walking (Kirkwood and Andrews, 1989). Michie also found that errors and inconsistencies would average out (he called this the "clean-up" effect) and the cloned system be more reliable than the human expert whose skill had been cloned. Similarly, Fuzzy Logic systems involve the use of "If...Then...Else" type rules to relate the inputs to the outputs, the same language used by a human expert to articulate his reasoning (Zadeh, 1973). Fuzzy controller uses membership functions to classify the inputs and outputs using linguistic variables such as low, medium and high. Therefore, the membership of the variables to each classification is graded. This kind of classification resembles that used by humans in the everyday classification of variables. In addition, the output control actions are continuous and more suited to the smooth control of the dynamic systems and modeling the continuous actions observed in the humans. The suitability of the fuzzy logic models for human control modeling have been demonstrated by applications such as modeling the motorcycle riding (Liu and Wu, 1993), car driving (Kramer, 1985) and acquisition of robot skills from human demonstration (Dillmann et al., 1995). It has also been argued that the concept of fuzzy logic control provides a useful and biologically compatible way of describing sensorimotor behavior (Prochazka, 1996). According to Jacobs, the human decision-making and control of movement does not generally rely on precise input-output data but instead it is compatible with imprecision and uncertainty inherent in the fuzzy logic systems (Jacobs et al., 1997c). He also argues that the fuzzy model is a good choice for modeling the postural coordination strategies in standing (Jacobs, 1997a). After all, the objective of the voluntary arm forces in paraplegic standing-up is primarily postural coordination.

Most reports aim to model the human operator as part of an industrial process in which the human can observe the state of the process by observing a visual display and then make corrective adjustments using manual controls. However, there are essential differences in paraplegic standing-up. The subject's own body is the process to be controlled, and present biofeedback displays are in an early stage of development and can only encode some of the system state variables using unnatural vibrotactile or electrocutaneous displays (Andrews et al., 1988; Petrofsky et al., 1984; Andrews et al., 1989; Graupe, 1989). Furthermore the system is decidedly multiple input multiple output (MIMO) by nature. It is not clear how the numerous sources of sensory information are used for decision making and there are many muscle activation strategies that can be used to produce the arm forces. Therefore, as a starting point, we have adopted an intuitive approach based on the use of fuzzy logic to model the voluntary force actions of the upper limbs. We identified key input and output variables and developed rules relating them based on previous biomechanical analyses involving paraplegic volunteers and our experience. A similar approach was used by Liu (Liu and Wu, 1993) to model the rider-motorcycle system and by Jacobs (Jacobs et al., 1997b) to model the postural coordination in standing. The use of a fuzzy logic model or expert system was selected over an experimentally identified linear system because human manual control is a highly nonlinear process and expert human knowledge can be directly articulated, or elicited by others, and documented as a fuzzy logic rule base that can be readily coded in a computer program. A fuzzy logic rule based model is also expected to provide a broader generalization and better local representation to cover the wide range of operation in standing-up motion.

3.2 Elements of the Proposed Model

The mathematical model is composed of four parts: muscle model, passive joint model, body segmental model, and a model of voluntary arm forces (Figure 3.1). The muscle model defines the overall output of the extensor or flexor muscle groups acting on the joint in response to the electrical stimulation. These muscle groups act as actuators of the artificial FES controllers. Passive joint model defines the behavior of the joint when all the muscles crossing the joint are relaxed such as the resistance of the knee joint to hyperextension. Physical properties of limbs including mass, center of mass, moment of inertia and the type of joints connecting the limbs are defined in body segmental model. The contributions of the subject arms are modeled by a fuzzy model of the voluntary arm forces.

3.2.1 **Muscle Model**

The muscle model represents the relationship between the stimulation input (pulse amplitude or pulse width), delivered to the muscle group and the generated torque about the respective joint. Only monoarticular muscles are included so that each muscle group affects primarily one joint in one direction (extension or flexion). Activation of the monoarticular muscles alone can be achieved by the implanted electrods but not the surface electrodes.

The number of the motor units fired in the muscle depends on the amount of the stimulation delivered. The recruitment curve describes this relationship. The curve is assumed to be linear with static non-linearity. The non-linearity includes deadband and saturation to account for the threshold stimulation and limited muscle output. The maximum torque decreases due to the fatigue. The first order dynamics with delay was used to model the muscle behavior. The computations of the muscle model can be summarized as follows:

The amount of the recruitment is calculated for the given stimulation level. The recruitment curve used for this purpose is defined as:

$$R = \begin{cases} 0 & S < S_{thr} \\ (S - S_{thr})/(S_{sat} - S_{thr}) & S_{thr} < S < S_{sat} \\ 1 & S > S_{sat} \end{cases} \tag{3.1}$$

Where,

R is the recruitment level (0-1).

S is the input stimulation.

S_{thr} is the threshold stimulation (minimum required to fire the first muscle fibers).

S_{sat} is the saturation stimulation that corresponds to the maximum muscle torque.

The maximum muscle torque, τ_{max} is discounted due to the fatigue using the following fatigue model (Durfee and Dilorenzo, 1990).

$$\tau_{maxf} = \tau_{max} \times (0.5 + 0.5e^{-t/t_f}) \tag{3.2}$$

Where,

τ_{maxf} is the maximum torque discounted due to the fatigue.

t is the time spent from the start of stimulation.

t_f is the fatigue time constant (time required for 32% decrease in muscle strength).

The torque generated as a result of the given stimulation is obtained as:

$$\tau_r = R \times \tau_{maxf} \tag{3.3}$$

τ_r is the raw torque generated by the muscle that acts upon the muscle-joint structure by a first order dynamics with delay defined as:

$$\tau = \frac{e^{-ds}}{1+Ts}\tau_r \tag{3.4}$$

Where,

τ is the overall torque generated by the muscle group about the respective joint.

d is the neurotransmission delay.

T is the time constant of the muscle dynamics.

3.2.2 Passive Joint Model

The behavior of the joint when all the muscles crossing the joint are relaxed is referred to as the passive joint dynamics. This behavior is due to the deformation of all tissues that surround the joint including skin, ligaments, tendons and relaxed muscles. The study of the passive joint dynamics were reported in the various literature (Franken, 1994; Yoon and Mansour, 1982; Mansour and Audu, 1986). The torque exerted by the passive joint structure has two components, elastic and damping torque.

Experimental data shows that the elastic torque is small for most values of the joint angle within a certain range ($\theta_1 < \theta < \theta_2$) while the torque rises sharply as the joint limits are approached. Sum of two exponentials is proposed to model this behavior (Mansour and Audu, 1986; Davy and Audu, 1987).

$$\tau_{pe} = k_1 e^{-k_2(\theta-\theta_2)} - k_3 e^{-k_4(\theta_1-\theta)} \tag{3.5}$$

The damping torque across the joints are modeled with a linear model of the form,

$$\tau_{pd} = -c_1\,\dot{\theta} \tag{3.6}$$

In the above equations,

τ_{pe} is the passive elastic torque.

τ_{pd} is the passive damping torque.

θ is the joint angle.

$\dot{\theta}$ is the joint angular velocity.

$\theta_1, \theta_2, k_1, k_2, k_3, k_4, c_1$ are joint specific constants that are adopted from (Davy and Audu, 1987).

3.2.3 Body Segmental Model

Body segmental model defines the segments of the body and the types of connections among them (Figure 3.2). The torque generated by muscles, voluntary forces and external forces act upon the body segments and joints and result in the total body motion. The following assumptions are made to keep the model manageable.

The body segments and their inter-connection is modeled by a planar system in sagittal plane. This assumption is based on the domination of the sagittal plane motion in paraplegic standing-up. It is assumed that the left and right body segments are similar and are stimulated with equal intensity. Therefore, they can be represented by one segment in the model. The feet are assumed to be flat on the ground and the hands are fixed on the standing frame.

The body segmental model consists of five segments (i.e. shank, thigh, trunk-head, upper arm and forearm) that are connected by friction-less pin joints.

The mass center of each segment lies on the line connecting the two adjacent joints and its position does not change during the motion.

D'Alembert-Lagrange principle is used to formulate the equations of motion (Paul, 1979). The detailed derivations are given in appendix A. Anthropometric data for body segmental model were obtained from (Winter, 1990) and scaled to the total body mass and height (Table 3.2)

3.2.4 Fuzzy Control Model of Voluntary Arm Forces

A fuzzy control model is used to abstract the decision making process involved in the voluntary control of the arm forces. It is assumed that the subject has developed the required skills to control the arm forces to help in standing-up, the developed strategy has achieved a similar behavior and is time-invariant, the subject is fully attending the control and nothing diverts his/her attention and the control actions are not affected by parameters such as personality, motivation, state of mind, behavior in emergencies and skill development. Experimental observations support the idea that each subject develops his/her own strategy for the control of arm forces although it may change among the subjects (Moynahan, 1995). The voluntary control involves the use of many sensory inputs and the control actions are the excitation to the many actuating muscles in the upper extremities. We assumed that the whole process can be modeled by controllers that use limited measurable variables such as those representing the body position as the inputs and manipulate the shoulder joint forces as the controller outputs. The fewer number of the sensory channels are not limiting factors as long as they can adequately define the state of the controlled system, i.e., the subject's body. No matter how the upper extremity muscles are activated, their overall effect is equivalent to and can biomechanically be represented by the forces and moments at the shoulder joint. Although the inputs and outputs are different from the natural voluntary control of the arm forces, the overall effect can be made similar by defining the proper control rules (Prochazka, 1996). These assumptions not only reduce the number of controller variables but also simplify the definition of the control rules. It is much easier for example to define meaningful rules relating the position of shoulder joint to the shoulder forces than to the individual muscle forces in the upper body. In fact, recent findings confirm that the central nervous system (CNS) uses similar simplifications. Examples by Jacobs (Jacobs et al., 1997b) show that the CNS uses simplified strategies to control global variables instead of performing complex calculation for individual muscle forces. Therefore, it may be the case that the control strategies for the arms develop to control shoulder joint position instead of calculating individual muscle forces in the upper body.

The goals of the postural control system during standing-up is to maintain the center of gravity over the base of support and move the subject upward (Moynahan, 1995; Dietz, 1996). The voluntary arm forces in paraplegic standing-up are no exceptions to these rules and they contribute to the same goals. Therefore, we use two fuzzy controllers, one controls balance in sagittal plan and the other controls the upward progression by manipulating F_H and F_V in Figure 3.2. It is assumed that the balance controller keeps the center of gravity over the base of support. Direct manipulation of the position of the center of gravity is impossible but it can be controlled indirectly by controlling the horizontal position of the shoulder joint. Therefore, the inputs to the balance controller are the horizontal position and velocity of the shoulder joint and the output is the horizontal force applied to the shoulder joint. The inputs to the second controller (that helps in upward progression) are the vertical position and velocity of the shoulder joint and the output is the vertical force at the shoulder joint. Each fuzzy controller has three parts; fuzzification, rule sets and defuzzification. Five triangular membership functions are used to fuzzify each input and seven for each output (Figure 3.3). Because of the limited capacity of human operational memory, the number of fuzzy subsets is kept below seven (Liu and Wu, 1993). The center of area method is used for defuzzification. There are 25 rules for each controller (Table 3.3). The control rules are developed by intuition and experimental observations as described below.

For non-dynamic standing-up usually practiced by paraplegics, it has been seen that the shoulder joint is first moved to the foot support area and kept there until the end of motion (Dolan, 1997). According to these observations, the rules are defined to always move the shoulder joint toward the center of the foot support area. However the strength of the move, in addition to the deviation of the shoulder joint from the center of support area, depends on the velocity of the shoulder joint. For example, if the shoulder joint is far away from the center and is still moving away it should be forcefully moved back to the center, i.e.,

If X_{err} is PL **And** V_x is PL **Then** F_H is NL.

On the other hand if the shoulder joint is far away from the center but is coming back toward the center then little or no additional force is required, i.e.,

If X_{err} is PL **And** V_x is NL **Then** F_H is Z.

The definitions of the abbreviations are given in Figure 3.2, Figure 3.3 and Table 3.3. The rules for the balance controller are given in Table 3.3. According to the experimental observations (Dolan, 1997), the vertical shoulder joint force is always positive (upward direction). Therefore, the rules for the second fuzzy control is defined to only apply upward force when required. The requirement of the force is determined by the deviation of the shoulder joint velocity from a predefined setpoint and the position of the shoulder joint in vertical direction. The velocity setpoint is calculated at the beginning of the simulation by dividing the total vertical distance to be traveled by the shoulder joint to the total time of standing-up motion. The amount of the force is reduced as the subject moves closer to the standing posture. The rules for the upward progression controller are given in Table 3.3.

3.3 Computer Implementation

The simulation of the model is implemented using a C program and Labwindows/CVI software package (National Instrument, USA). The software provides a good user interface for changing the simulation parameters. A three dimensional stick-figure animation capability was developed to visualize the resulting motion. Variable step fourth order Runge-Kutta integration method was used to integrate the equations of motion.

3.4 Simulation Results

3.4.1 Standing-up without electrical stimulation

It was possible to perform standing-up maneuver without electrical stimulation of the lower extremities, assuming that enough amount of forces can be developed by the arms. The average upward force of 510 N was required for standing-up. A typical standing-up trajectory without electrical stimulation is shown in Figure 3.4. In this simulation, the knee and hip joints could not be extended fully and they tended to slightly oscillate at the end.

3.4.2 Standing-up without arm forces

In this experiment, while the arms are providing balance (no vertical arm force), the minimum joint moments for standing-up are investigated. Standing is achieved in three ways, activation of knee extensors only, activation of hip extensors only and activation of both knee and hip extensors. Knee and hip joint extensors were activated by open-loop constant level maximal electrical stimulation.

By stimulating only knee extensors, 105 N.m was required in each knee joint for a successful standing-up.

By stimulating only hip extensors, the minimum required torque in each hip joint was 148 N.m.

For stimulation of both the knee and hip extensors, different combinations were possible. Therefore, we fixed the knee joint torque at a moderate value of 65 N.m (0.92 N.m/KgBW) and calculated the minimum compensatory torque at the hip joint. As the result, the minimum torque at each hip joint was 55 N.m (0.78 N.m/KgBW).

3.4.3 Standing-up with arm force and open-loop stimulation of knee extensors

With stimulation of the knee extensors with maximal stimulation to produce a typical torque of 65 N.m, the average upward arm force was 227 N for both arms. Simulation shows that 1 N.m decrease in knee torque can be compensated by 1.8 N increases in the average upward arm forces. A typical standing-up trajectory with arm forces and open-loop control of knee joints is shown in Figure 3.5.

3.5 Discussion

By controlling the position of the shoulder joint, it was possible to assume standing posture even without the help of the lower extremity. However, it required high amount of forces by the arms. As can be seen in many paraplegics, it was possible to perform standing-up maneuver without electrical stimulation of the lower extremities. The predicted average upward arm force of 510 N was close to the reported value of 532± 26 N in (Dolan, 1997; Dolan et al., 1998).

Upper body forces have two primary objectives, providing balance to prevent falling and providing additional upward force when the forces in stimulated paralyzed muscles are inadequate. These two tasks must be taken care of if unassisted standing-up is to become a reality. Upward arm forces can be eliminated only if enough amount of torques can be produced by electrical stimulation of the paralyzed muscles. Balancing task however, is much more complicated. It requires sophisticated controllers to coordinate the movements of all the limbs in a way similar to normal standing-up. Therefore, we left the arms to provide balance, and investigated the possibility of standing-up without applying upward arm forces.

Assuming that balancing arm forces keep the shoulders in appropriate position around the feet support area, it was possible to stand-up by activation of knee extensors, hip extensors or both. This scenario is similar to paraplegic standing-up where, the center of gravity is moved over the feet support area before taking-off from the chair. It is also different from normal standing-up, which is more energetic.

The values reported for the torque production capacity of the electrically stimulated knee extensors varies considerably among paraplegic subjects. The values of 24 N.m in (Dolan et al., 1998), 40 N.m in (Quintern et al., 1989), 30-100 N.m in (Kralj and Bajd, 1989) and 38-54 in (Kagaya et al., 1995) have been reported. According to these data, in knee only stimulation strategy, paraplegics will not be able to produce 105 N.m in each knee joint and upward arm forces will be required. The reported knee joint torques for standing-up in healthy young and healthy elderly are 130 N.m and 115 N.m respectively (Schultz et al., 1992).. These values are higher than 105 N.m predicted by our model. This difference seems to be due to the differences in standing-up strategies. In our model trunk is initially flexed to simulate paraplegic standing-up. Therefore, the knee torque requirement is lower. In general, paraplegic standing-up is closer to that performed in elderly because both are less energetic. Therefore, our model, which was less energetic and used an initially flexed trunk, required less knee torque.

To our knowledge, there are no data available for the torques produced by the electrically stimulated hip joint. However, estimation can be made by comparing the values of knee and hip torques in normal subjects. In normal subjects hip extensor moment is about 5/6 of knee moment (Hoy et al., 1990; Schultz et al., 1992). By extending this ratio to paraplegics, the achievable hip torque will be around 20-83 N. This value is much lower than the required 148 N.m hip extension torque and as a result, hip only stimulation strategy does not seem to be possible.

Comparing the knee only and hip only strategies shows that the same amount of torque produced in knee joint is more effective than that in the hip joint. The ratio is 105 to 148 or 1 N.m in knee joint is as effective as 1.41 N.m at the hip joint, as far as the minimum joint torque is considered.

The results show that the deficiencies in knee torque can be compensated by the hip joint torque. Stimulation of both knee and hip demands less torque from each of the joints. The knee and hip torques predicted for this experiment closely resembles the experimental values of 0.9 N.m/KgBW and 0.7 N.m/KgBW observed by Kotake et al. (Kotake et al., 1993).

Standing-up with open-loop control and arm force, required in average, 227 N upward arm force for both arms. Mulder et al. (Mulder et al., 1992), reported that minimum of 250 N was required for standing-up with the knee torque of 75 N.m. Dolan et al. (Dolan et al., 1998) reported an average arm force of 332 N for a subject weighing 56 kg that could produce 24 N.m knee torque. Therefore, the arm force requirement is a function of available knee torque, weight and initial position of the segments. Even when all these parameters are equal, the patients may load their arms differently depending on how they rely on FES to provide the leg support. For example, patients entering FES standing-up programs usually put more load on their arms before they learn to trust the FES and load the legs.

The general agreement between the model predictions and the reported data in the literature suggests that the simple model developed here may provide an appropriate test environment for further improvements in FES control techniques in a controlled environment.

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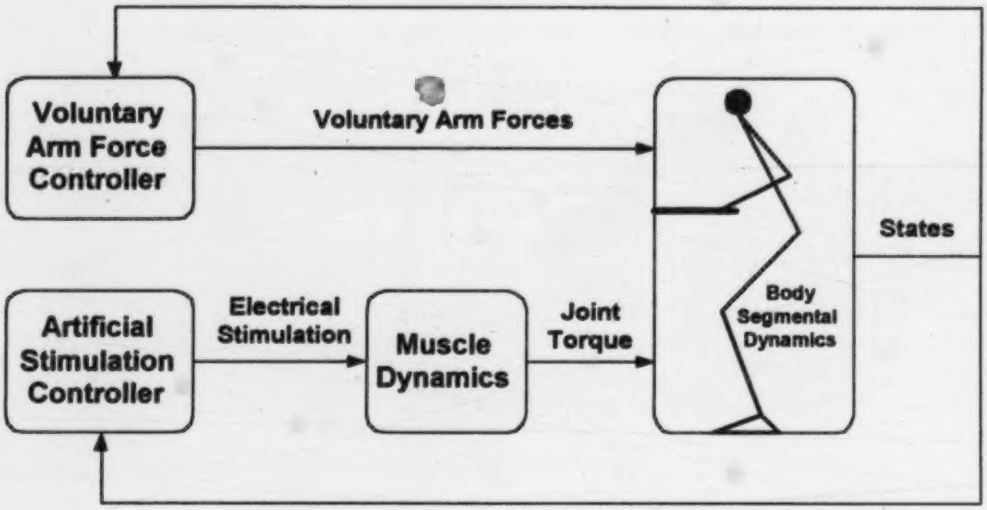
Voluntary Arm Force Controller
Voluntary Arm Forces
States
Artificial Stimulation Controller
Electrical Stimulation
Muscle Dynamics
Joint Torque
Body Segmental Dynamics

Figure 3.1 The main components of the mathematical model of standing-up in paraplegia.

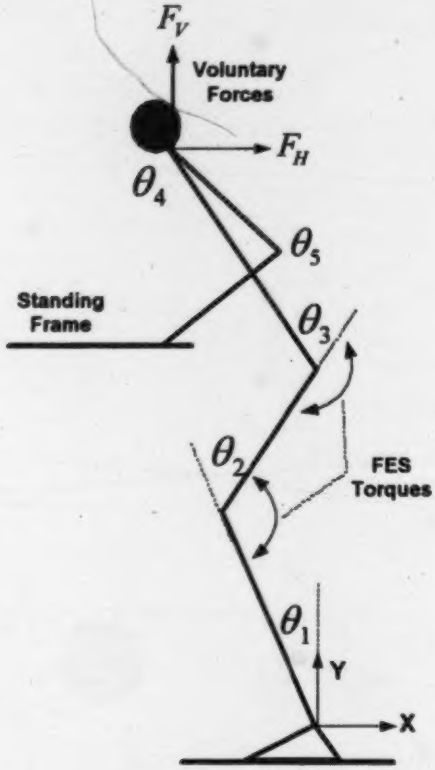
F_V
Voluntary Forces
F_H
θ_4
θ_5
Standing Frame
θ_3
θ_2
FES Torques
θ_1
Y
X

Figure 3.2 Body segmental model of the arm-assisted standing-up. θ_i's are the angular positions of the segments measured from the previous segment (dashed lines). The dynamics of the arms is divided into active and passive part as explained in the text. Mass, length, location of the center of mass, and radius of gyration for segments is given in Table 3.2.

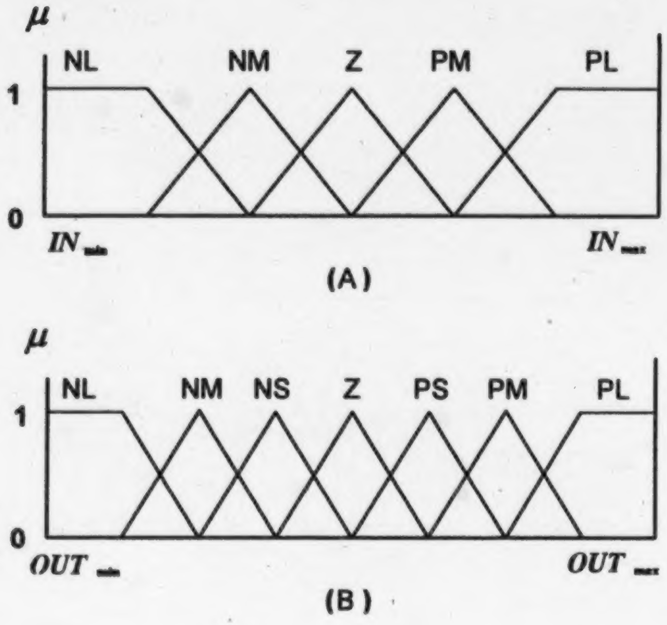
μ
NL
NM
Z
PM
PL
1
0
IN min
IN max
(A)
μ
NL
NM
NS
Z
PS
PM
PL
1
0
OUT min
OUT max
(B)

Figure 3.3 Membership functions for fuzzy control model of the voluntary arm forces. (A) represents the membership functions for inputs and (B) for outputs. Input variables spanning between IN_{min} and IN_{max} and output variables spanning between OUT_{min} and OUT_{max} are classified with five and seven fuzzy subsets respectively. N - Negative P - Positive Z - Zero S - Small M - Medium L - Large V - Very

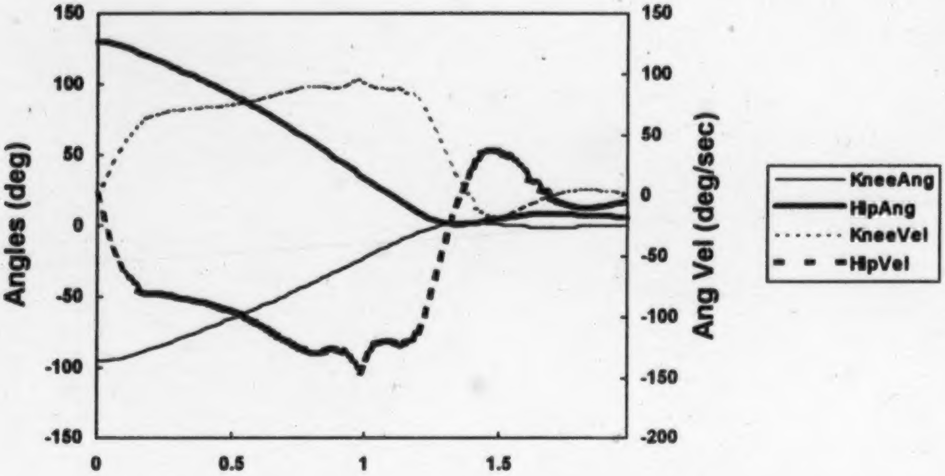

Figure 3.4 Typical joint trajectories for standing-up without electrical stimulation. Stabilizing and upward voluntary forces are the only applied forces.

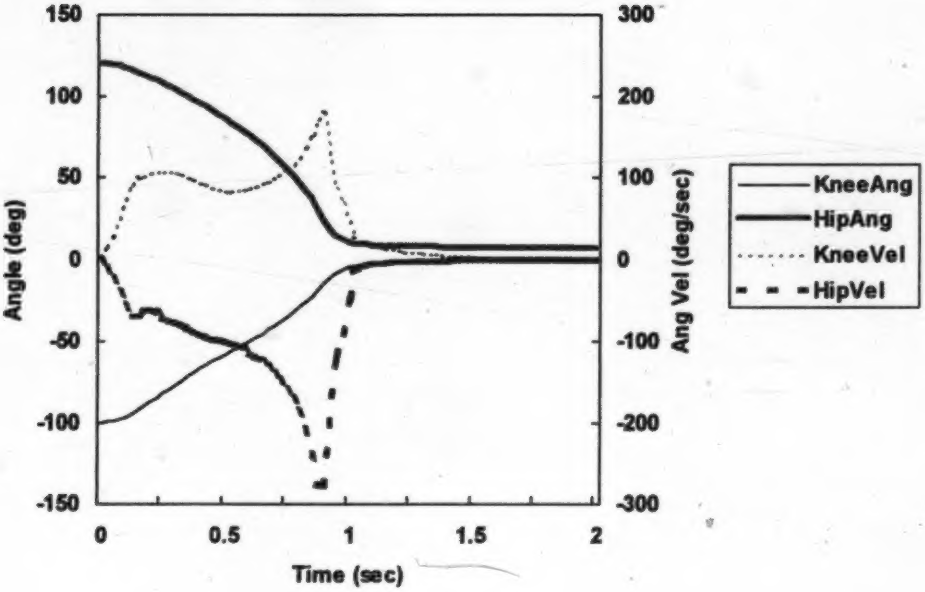

Figure 3.5 Typical joint trajectories for standing-up with arm forces and electrical stimulation. Preset maximum constant level stimulation is delivered to knee extensors in open-loop manner.

Subject mass, M	70.0 kg
Subject height, H	1.75 m
Muscle fatigue time constant, t_f	105 sec
Muscle time constant, T	30 ms
Stimulation delay, d	50 ms
Initial Ankle angle, θ_1	15°
Initial knee angle, θ_2	-95°
Initial Hip angle, θ_3	130°
Integration time step	0.01 sec
Maximum knee extensor torque	65.0 N.m
Maximum knee flexor torque	32.5 N.m
Maximum hip extensor torque	55.0 N.m
Maximum hip flexor torque	27.5 N.m

Table 3.1 Model parameters for the computer simulation of standing-up.

	Shank **1**	**Thigh** **2**	**Trunk** **3**	**Upper-Arm** **4**	**Fore-Arm** **5**
m	0.0465M	0.1M	0.578M	0.028M	0.016M
l	0.246H	0.245H	0.288H	0.186H	0.146H
l_c	$0.567l_1$	$0.567l_2$	$0.66l_3$	$0.436l_4$	$0.43l_5$
ρ_c	$0.302l_1$	$0.323l_2$	$0.503l_3$	$0.322l_4$	$0.303l_5$

Table 3.2 Anthropometric data for the model of standing-up. M is the total body mass, H is the subjects' height, ***m*** is the mass of segment, ***l*** is the length of the segment, l_c is the position of segment mass center and ρ_c is the radius of gyration.

(A) Control rules for F_X

V_X $X-X_C$	**NL**	**NM**	**Z**	**PM**	**PL**
NL	PL	PL	PM	PS	Z
NM	PL	PM	PS	Z	NS
Z	PM	PS	Z	NS	NM
PM	PS	Z	NS	NM	NL
PL	Z	NS	NM	NL	NL

(B) Control rules for F_Y

V_Y-V_{SET} Y	**NL**	**NM**	**Z**	**PM**	**PL**
VS	PL	PL	PM	PM	PM
S	PL	PM	PM	PM	PS
M	PM	PM	PM	PS	Z
L	PM	PM	PS	Z	Z
VL	PM	PS	Z	Z	Z

Table 3.3 The rule base of the fuzzy logic controllers of the voluntary arm forces. The control rules are for F_X (A) and F_Y (B). X, Y, V_X and V_Y are the position and velocity components of the shoulder joint in the coordinate system shown in Figure 3.2. $X_C = -0.1$ m (center of the foot support area) and $V_{SET} = 0.35$ m/sec are used as setpoints for the horizontal position and the vertical velocity of the shoulder joint. The outputs of the controllers are the normalized F_X and F_Y that are then linearly scaled to their maximum values. The maximum values of F_X and F_Y are set at 150 N and total body weight respectively. N - Negative P - Positive Z - Zero S - Small M - Medium L - Large V - Very.

4 Comparative Study of Fixed-Parameter Controllers In FES-Assisted Standing-up

4.1 Introduction

Previous FES applications have demonstrated the feasibility of standing and walking after spinal injury (Phillips, 1991; Kralj and Bajd, 1989; Graupe, 1994; Phillips, 1991). Standing-up is important because it is a prerequisite for many of the daily life activities such as the initiation of walking, reaching down high objects, making transfers and interaction with other people face to face. In addition to function, frequent FES standing may provide therapeutic benefits such as the prevention of muscle atrophy, contractures, bone demineralization, ectopic ossification as well as improving leg blood flow and spasticity (Kralj and Bajd, 1989; Andrews and Wheeler, 1995).

Kralj and Bajd (Kralj and Bajd, 1989) proposed a procedure, now widely adopted clinically, for standing up using upper body assistance and bilateral stimulation of the knee extensors. The arms and upper body, particularly the preserved lattisimus dorsi, can generate force actions that react through the handgrips of a stable support frame to compensate for any deficiency in FES generated knee torque. Preset constant level stimulation results in a pattern of knee extension torque that differs significantly from the normal profile in which initially, a high peak torque is generated to lift-off the seat, is then followed by a progressive reduction in torque as the knee extends. This produces a smooth deceleration of the knee joint to low angular velocity just before full extension (Doorenbosch et al., 1994; Kelly et al., 1976). In practice, the intensity of the constant stimulus is usually adjusted to reach a compromise between reducing the KEV and the amount of upper limb effort required to lift-off the seat. Although the technique is simple and works adequately for many people, there is an excess of stimulation that contributes to muscle fatigue and higher than normal knee end velocity (KEV). In addition, there is a requirement for significant upper limb force actions that can exceed two-thirds of body weight (Dolan, 1997). The latter is of concern because over time the cumulative effects of transfers and wheeling can cause or exacerbate arm injury and pain due to overuse (Bayley et al., 1987; Chisholm, 1997). High KEV may also be a concern since it is not known if such repetitive insults to the ligaments may ultimately lead to damage - it is the ligaments that absorb all the energy in bringing the leg to a rapid and jerky halt.

A number of improved control schemes have been claimed that usually involves some measure of feedback and are sometimes supported by limited laboratory trials. However, the paucity of data does not allow objective comparison. There are too many controller and patient variables to make clinical comparisons feasible and cost effective. An alternative would be to devise a computer model of the sit-stand maneuver and then use this to compare the performance of controllers against some defined criteria. This approach would make available a repeatable test-bed that others could adopt and at least narrow the choice in preparation for costly and time consuming clinical evaluations. Unfortunately, all the previously reported models had some limitations for our application particularly the unrealistic modeling of the voluntary upper body and limb force actions and the use of open rather than closed chain dynamics. Here we outline the development of a new biomechanical model and present the results of a quantitative comparison of five promising candidate FES controllers selected from the literature. Preliminary reports of this work have been previously reported (Davoodi and Andrews, 1996a; Davoodi and Andrews, 1996b).

4.1.1 Feedback Controllers for FES Assisted Standing Up

Petrofsky (Petrofsky et al., 1984) used a linearly increasing stimulus intensity from the start of the maneuver followed by a constant level of stimulation of the knee extensors whilst standing. The measured knee angle was used to detect full leg extension and minor improvements were observed compared with the method of Kralj & Bajd. Ewins (Ewins et al., 1988) used two different PID FES controllers for standing up and maintaining standing respectively because faster response was required in the latter. Quintern

(Quintern et al., 1989) used a combination of closed-loop PID and an open-loop feedforward control. The feedforward control signal was either a simple ramp up of FES intensity or was calculated using a model of standing-up. Andrews (Andrews, 1990) and Mulder (Mulder et al., 1992) applied closed-loop on/off control based on a phase plane switching curves of the desired knee velocity versus knee angle. A bell shaped switching curve similar to that used by Andrews is shown in Figure 4.2. The stimulation was turned on/off by comparing the actual knee velocity and angle to the switching curve. In comparison to the basic maximal stimulation of the knee extensors, considerable improvements were reported in decreasing the KEV and the amount of stimulation but total time was longer and more arm force was required. In a recent study, Dolan (Dolan, 1997) has conducted a thorough study of the different switching curve strategies.

There have been no comparative studies of these controllers to suggest which scheme one should choose for FES standing-up in paraplegia. The variation between patients and in any single subject together with the number of factors involved suggests the use of a computer model of paraplegic standing-up.

4.1.2 Computer Models of Paraplegic Standing-up

Because of the unpredictable nature of voluntary force actions, standing-up experiments on paraplegic are essentially unrepeatable. Therefore, clinical laboratory comparison of the different control strategies would require too many repetitions of the trials to be practical. On the other hand, a computer model provides a test bed, i.e. a controlled environment to compare different strategies. Mathematical models of FES standing have been developed with various degrees of complexity. Jaeger (Jaeger, 1986) reported a three segmental static model and a single link dynamic model used to study the restoration of quiet standing by FES control of the ankle joint motion. The motion was controlled only in the close vicinity of the vertical standing posture and the upper limbs were ignored. Khang (Khang and Zajac, 1989a; Khang and Zajac, 1989b) modeled the standing-up motion by a planar four-segment system (i.e. foot, shank, thigh and trunk-head). The feet were assumed to be flat during the motion and upper extremity force actions were treated as external disturbances and replaced by horizontal force, vertical force and a moment acting at the shoulder. Veltink (Veltink et al., 1995) also proposed a three segmental model of standing-up in which the arm forces were modeled by linear proportional control laws with a vertical velocity and a horizontal position setpoint.

4.2 Methods

Biomechanics of the paraplegic standing-up is represented by a planar model in sagittal plane. The model is composed of four parts: body segmental model, muscle model, passive joint model and a model of voluntary arm forces (Figure 4.1). Body segmental model is composed of five segments, shank, thigh, trunk-head, upper arm and forearm that are connected via friction-less pin joints in a closed chain configuration. The knee and hip joints are driven by electrical stimulation of their extensors and flexors. The shank plantar flexion is limited by an ankle foot orthosis (AFO). Initially the shank is flexed forward by pressing over the AFO but gradually moves to the vertical position and stays there. The shank angle moves from the flexed position to the vertical as a function of the knee angle in a prescribed motion. The mass center of each segment lies in the line connecting the two adjacent joints. Anthropometric data are obtained from (Winter, 1990) and scaled to total body mass and height. The torque actions of the extensor and flexor muscles in response to the electrical stimulation are modeled by first-order dynamics including static nonlinearities, time delays and fatigue model. The torque exerted by the passive joint structure has two components, elastic and damping torque. Sum of two exponentials is used to model the elastic component. The damping torque across the joint is modeled with a linear function of the joint velocity. The overall arm force actions are represented by a horizontal and a vertical force acting on the shoulder joint. The voluntary control of these forces is modeled by handcrafted Fuzzy Logic controllers. The model parameters are given in Table 4.1. Details of the model development and its validation can be found in (Davoodi and Andrews, 1996a).

D'Alembert-Lagrange principle is used to formulate the equations of motion (Paul, 1979). The detailed derivations are given in appendix A. 4th-order variable step Rung-Kutta method was used to integrate the equations of motion. The fuzzy controller model of the voluntary arm forces is developed using the Matlab Fuzzy Logic Toolbox (The MathWorks Inc., USA). The equations of motion, fuzzy model of the voluntary arm forces and the algorithms for the controllers are all implemented using C programming language and the LabWindows/CVI environment (National Instrument, USA). The simulation program provides the user with a useful user interface for changing the simulation parameters and has an animation facility for presentation of the resultant motion.

4.2.1 FES Controllers Tested

The following five control strategies are compared:

OPENMAX: Open-loop maximal stimulation of the knee extensors (Kralj and Bajd, 1989).

OPENLIN: Open-loop linear ramp up of stimulation to the knee extensors (Petrofsky et al., 1984; Jaeger et al., 1989).

SCURVE: Switching curve On/Off control (Andrews, 1990; Dolan et al., 1998; Mulder et al., 1992).

PID: Proportional integral derivative controller (Ewins et al., 1988).

FUZZY: Fuzzy logic controller (Cox, 1994).

In OPENMAX, the stimulation to the knee extensors was set to its maximal value during standing-up. In OPENLIN, the intensity of stimulation to the knee extensors was ramped-up linearly to its maximum and then kept constant.

The next three strategies are closed-loop methods. SCURVE strategy switches stimulation on/off after comparing the actual velocity and angle of the joint with the reference switching curve. A trajectory similar to the one in normal subjects is used as the switching curve. It has zero velocities at the start and termination of standing-up (Figure 4.2). The stimulation is turned On when the actual velocity is lower and turned off when it is higher than the reference velocity. For example, when the knee joint is in position θ_1, if the knee joint velocity is lower than the switching curve velocity (e.g. ω_1), the stimulation to the knee extensor muscles will be turned on but if it is higher (e.g. ω_2), the stimulation will be turned off (Figure 4.2).

PID is the standard proportional integral derivative controller. It attempts to follow the reference trajectories for the joints' angle and angular velocity. According to the results of our previous study (Davoodi and Andrews, 1996a), we decided not to use the reference trajectories normally used in robotics. These trajectories are functions of time and the maneuver must end in a fixed time that was shown to be inappropriate for FES standing-up. Instead we determine the reference joint velocity from the switching curve shown in Figure 4.2 and use the angular positions of the joints in standing position as the reference joint angles. As the result the reference trajectories are not functions of time and the maneuver could be performed in more or less time depending on the limitations of the subject. The inputs to the controller are the errors between the reference and actual trajectories and the output is the stimulation to the joint extensors and flexors. Where it is desired to only stimulate extensors, we neglect the controller outputs that are normally sent to the flexors. The controller constants are tuned manually using the computer simulations.

Fuzzy logic controllers (FUZZY) are rule-based systems that use fuzzy linguistic variables to model a human rule-of-thumb like approach to problem solving. They are universal function approximators and are specially suited to nonlinear and complex systems that would otherwise be difficult to model and control by conventional methods. Fuzzy systems include membership functions to convert the linguistic variables like "low" and "high" into precise numeric values needed by a computer and rules to direct the decision process. The output of the fuzzy controller is determined in three steps. In the fuzzification step, crisp values of input variables are converted to the fuzzy membership values. Memberships of the output fuzzy sets are then found for all the rules relating the inputs to the outputs. Finally in the defuzzification step, the memberships of output fuzzy sets are converted to a crisp value as the controller output. We use two controllers in the knee and hip joints. Each controller has two inputs (angular position and angular velocity) and one output (electrical stimulation). The design process includes the selection of the shape and the number of the membership functions for the input and output variables and the rules directing the decision process to achieve the desired performance. There are no reference trajectories and the controllers are designed to reduce the arm forces and the KEV. Both the angular positions and angular velocities are represented by 6 triangular membership functions. The output variable is represented by 36 (6×6) singleton membership functions (Cox, 1994). There is one rule for each combination of the input variables resulting in 36 rules. Therefore, the consequent part of each rule is effectively the value of a singleton membership function.

We tuned the rules (or value of the singletons) and the input membership function by trial-and-error method.

4.3 Simulations Results

The dynamics of the arm-assisted standing-up is affected mainly by the voluntary arm forces, the FES generated torques in the lower extremity joints and the gravity forces. Gravity forces tend to collapse the subject and must be countered by the voluntary arm forces and the FES that cooperatively move the subject from sitting to standing position.

Because of the closed-form configuration and the presence of the AFO, there are only two degrees of freedom in the planar model of the arm-assisted standing-up (Figure 4.1). Therefore, standing-up can be realized, at least in theory, by controlling only two degrees of freedom. Scenarios such as actuating knee and hip joints, elbow and shoulder joints or shoulder and knee joints are possible. Availability of the redundant actuators makes it possible to compensate for deficiencies in the weaker actuators by the others. On the other hand, only knee and hip joints can be actuated by FES leaving upper body joints to the voluntary control that is assumed to behave in a cooperative manner with the FES control in the Man-Machine system.

Criteria for comparison of the different control strategies are indices representing the arm force, total electrical stimulation, the time of standing-up, KEV, robustness to the physical parameters and disturbances, smoothness of the joint trajectories and the complexity of the controller design.

Different scenarios combining FES and arm forces will be investigated. Then a common practice employing the FES control of the knee extensors along with the application of the arm forces will be used to compare five different FES control strategies. Finally, a scenario employing all the FES and voluntary actuators will be used to compare different control methods. In all the simulations, the balancing arm forces will be present to prevent the subject from falling while the upward arm forces may or may not be applied.

4.3.1 Standing-up Without FES

As discussed above and also seen in practice, paraplegics can stand up using only voluntary arm and upper body forces with no FES. The objective here was to find the minimum arm forces required.

Simulation trials showed that the average force required of each arm for a successful completion of the standing-up was 255 N (3.64 N/KgBW).

4.3.2 FES Standing-up with no Vertical Arm Force

The balancing arm forces were present but the upward arm forces were not applied. Open-loop FES was applied to the knee joint, hip joint or both. The objective was to find the minimum joint torques for FES only standing-up. Knee and hip joint extensor muscles were activated by open-loop constant level maximal stimulation.

For knee only stimulation strategy, the minimum knee torque required for successful standing-up was 105 N.m (1.5 N.m/KgBW). Hip only stimulation strategy requires at least 148 N.m (2.1 N.m/KgBW) in each hip joint. When stimulating both knee and hip joints, different combination of the joints' torques were possible but a typical minimum requirement was 65 N.m (0.92 N.m/KgBW) for the knee joint and 55 N.m (0.78 N.m/KgBW) for the hip joint. The results are summarized in Table 4.2.

4.3.3 Standing-up with Arms Forces - Knee Extensor Stimulation

This strategy is popular in FES clinics and laboratories. It represents the minimal configuration for the FES standing-up and is simple to perform. Five FES control strategies were used to control the knee extensor muscles. The performance of these controllers are compared in similar test condition that is provided by using similar criteria for detecting the initiation and termination of standing-up and similar voluntary control strategy.

Typical simulations are shown in Figure 4.3 - Figure 4.5 and the performances of the controllers are summarized in Table 4.3.

4.3.4 Standing-up With Arms Forces - Knee and Hip Stimulation

Full control of the knee and hip joints are expected to result in lower arm forces and better control over the joint trajectories. Both extensor and flexor muscles of the knee and hip joints are stimulated. Here again five FES control strategies were used to control both the knee and hip joints.

The performances of the controllers are summarized in Table 4.4. The performance of the PID and FUZZY control strategies are shown in Figure 4.6 and Figure 4.7 respectively.

4.4 Discussion

4.4.1 Standing-up without FES

Standing-up without FES required large forces from the arms. In practice these must be reduced to avoid overuse injuries and pain and to potentially extend the use of FES standing to those with upper limb impairments or obesity and the frail elderly spinal injured.

4.4.2 FES Standing-up with no Vertical Arm Force

Here the conditions for reducing the upward arm forces to zero were investigated. It was found impossible to stand-up using stimulation of knee or hip joint alone. In Table 4.2 the minimum torque requirement (105 N.m for knee and 148 N.m for hip) appear to be greater than FES torques previously reported e.g. isometric knee joint torques are typically less than 90 N.m (Kralj and Bajd, 1989; Dolan, 1997; Carroll et al., 1989; Marsolais and Kobetic, 1983). Brindley (Brindley et al., 1979) reported that with the same degree of training and stimulation frequency the hip extension torque could never exceeded one-tenth that of the knee extensor torque. The authors are unaware of reports quantifying FES induced hip joint torque, however, we doubt that 148 N.m could be achieved.

Knee stimulation is preferred to hip stimulation because in similar conditions the torque applied at the knee joint is 1.4 times more effective than the hip joint. This may be deduced by comparing the minimum torque requirements, i.e., in Table 4.2, it can be seen that the knee only standing-up requires 105 N.m whilst hip only standing-up required 148 N.m.

FES only standing-up may be effected by stimulating simultaneously both knee and hip joints as can be observed from Table 4.2. In this case, the joint torques requirements are lowered and one joint can compensate for the other. This is further illustrated in Table 4.2 for one case in which 65 N.m was required at the knee joint and 55 N.m at the hip joint.

4.4.3 Standing-up with Arm Forces - Knee Extensor Stimulation

Combining FES with arm forces provides redundant actuators, making it possible to trade off among the actuators and optimize the whole maneuver for certain objectives. For example, applying more intense stimulation to the knee and hip muscles can reduce arm forces. Stimulating only the knee extensors can reduce arm forces by an amount that depends on the FES control strategy used (Table 4.3). If the FES controller is slow to act then the upper limbs would have to make up the shortfall in the force actions required to stand up.

From Table 4.3, it can be seen that the OPENMAX controller resulted in an average arm force of 133 N, i.e., about half the 255 N required for arm only standing-up. Therefore, the stimulation of the knee joint extensors considerably reduces the arm forces. The arm force requirement of the OPENMAX is also the lowest in Table 4.3 indicating that it is the most aggressive controller. However, the amount of electrical stimulation delivered and the KEV are the highest.

The arm forces observed in Table 4.3 for the OPENLIN controller are slightly higher than those for the OPENMAX controller. This is because of the low-levels of stimulation applied during the ramp-up, when the demand for the joint torque is high. Consequently, higher arm forces are required to maintain an upward motion. Compared with OPENMAX, the KEV remains almost unchanged but the amount of stimulation delivered is slightly reduced. Therefore, OPENLIN does not offer significant improvement over the OPENMAX controller.

It can be seen from Figure 4.5 that the simplest closed-loop control, SCURVE, acts much slower than OPENMAX resulting in a 48.3% increase in the time of maneuver and the highest average arm force at 54% more than OPENMAX. However, the KEV is reduced by half, as indicated in Figure 4.5, and from Table 4.3 it can be seen that the average stimulation is reduced by 51.6%.

The PID controller required 33.1% less arm force and 24.1% less stimulation than SCURVE. PID control also reduced the KEV by 29.5%. However, compared with OPENMAX, arm forces were higher and KEV considerably lower.

The results shown in Table 4.3 clearly show that the FUZZY controller demonstrated improvements on all performance measures over PID control. FUZZY applied 6.4% less stimulation and 15.4% less KEV. Compared to the OPENMAX, the average arm force was 7.5% higher, however, the amount of stimulation was reduced by 57.8% and the terminal knee velocity was significantly reduced by a factor of 70%. This was only one of the possible designs for the FUZZY controller. Its numerous adjustable parameters allow it to produce different behaviors but it is difficult to tune them optimally by the trial and error method used here.

4.4.4 Standing-up with Arms Forces - Knee and Hip Stimulation

In the previous section, because of the lack of stimulation, the hip joint could not be maintained fully extended in the upright standing position. Paraplegics solve this problem by adopting the C posture in which the center of mass of the upper body is located posteriorly with respect to the hip joints. In this posture, characterized by an exaggerated lordosis, the hip joint is maintained hyperextended against the iliofemoral ligament. Stimulation of the hip extensors was found to further reduce arm forces and lessen the demand for knee joint torque. Again, the effect of hip stimulation was found to vary depending upon the FES control strategy used.

Comparing the results of Table 4.3 and Table 4.4 indicates that hip joint stimulation reduced the arm forces and time to stand-up but increased the amount of stimulation for all the controllers. For the OPENMAX controller the KEV increased by 38.5% whereas the closed-loop methods were able to maintain a low terminal velocity. In Table 4.4, the OPENMAX again produced the lowest arm forces, but the highest KEV and amount of stimulation. However, the closed-loop strategies were not able to reduce the arm forces to the level of OPENMAX without compromising their low KEV.

4.4.5 Robustness, trajectory smoothness and implementation efforts

Robustness to the error in physical parameters and disturbances is investigated by changing the simulation parameters. As mentioned before, paraplegic standing-up employs redundant actuators including voluntary and FES actuators. This redundancy of actuators and the comparatively high arm forces result in a high degree of system robustness. For example, the arm forces can compensate for limited FES muscle force. The same is true for the internal and external disturbances and parameters such as subject mass and height. The arm forces in paraplegics are well developed mainly because of the use of wheelchairs. However, the robustness will diminish for individuals with upper limb impairments.

Open-loop strategies result in relatively high KEV but the trajectories are smooth elsewhere. On/Off nature of SCURVE results in more uneven trajectories during standing-up. The KEV is lower but the oscillatory behavior is seen at the termination of standing-up where SCURVE has difficulty in locking the knee joint (Figure 4.5). The continuous control actions in PID result in smoother trajectories but there are still oscillations at the terminal phase (Figure 4.6). FUZZY control results in smoother trajectories and better control of the terminal phase (Figure 4.7). We suppose that smoother trajectories may be preferred by paraplegics for cosmetic reasons. The potential for joint damage due to high terminal velocities is not yet known.

In terms of design and implementation, OPENMAX and OPENLIN are clearly simpler with no need for feedback sensors and few design issues. All closed-loop methods require feedback sensors that add additional encumbrance. In the above systems, hip and knee angles were used. The lack of durable low profile sensors is often cited as being a major limitation to the deployment of feedback for routine application. For example, traditional motion measuring devices such as the popular Penny and Giles flexible goniometer (Penny and Giles Biometrics Ltd., UK), whilst suitable for laboratory use, are too fragile and difficult to keep in place for everyday use. New possibilities are being explored for the new generation of miniature and robust micromachined accelerometers and rate gyroscopes (Andrews and Williamson, 1997). Among closed-loop methods, SCURVE is easier to implement because its design requires only that a generic switching curve be defined. Tuning the PID controller requires moderate skill and effort especially for standing-up where, the dynamics changes substantially during the motion. It was found that a single PID controller could not perform equally well over the whole range of the sit-stand maneuver. One possible solution is to use a gain-scheduling technique and in the next chapter, we will explore this possibility. The FUZZY control was the most difficult to design and implement. The PID controller had only three design parameters compared with the 36 rules and 12 membership functions for each joint's fuzzy controller that must be tuned. FUZZY is also computationally much more costly than either the SCURVE or PID and requires special measures for real-time implementation.

4.5 Conclusions

A more realistic computer model is now available and provides a consistent test-bed environment in which candidate FES control strategies for paraplegic standing-up can be compared. The simulations indicated that it is possible for a paraplegic to stand-up using only his arms, as can be observed clinically. In addition, the model suggested that it might be possible to stand up using only FES and zero arm forces.

The classical open-loop controller of Kralj and Bajd produced the highest terminal velocities in the knee joints and used the most electrical stimulation. However, it resulted in the shortest standing-up time and the smallest arm forces. Open loop controllers are inherently easier to synthesize than closed-loop types. The latter require reliable and unobtrusive feedback sensors for everyday use, which are not readily available at present. These closed loop controllers must be set up and tuned for proper performance adding expense in terms of expertise and time for routine clinical fitting and patient training.

All three closed-loop methods decreased the KEV considerably at the expense of increasing the time to stand-up. They also decreased the total amount of stimulation but increased the magnitude of the required arm forces. The SCURVE method gave the longest standing-up time and highest arm forces and showed oscillatory behavior at terminal phase of motion. It was difficult to tune the constants of the fixed parameter PID to effectively control both standing-up and maintain standing although the technique of gain scheduling may result in improved performance. The FUZZY controller was the most difficult to design and implement because of the numerous parameters that required tuning. However, its nonlinear structure and its capability for different control behaviors in different regions of the state space make it suitable for effective control of standing-up as well as maintaining standing. The results and our experience suggest that the tuning of the parameters of the FUZZY controllers and gain-scheduling PID controllers could be improved leading to further performance enhancement. The latter will be investigated in the next chapter.

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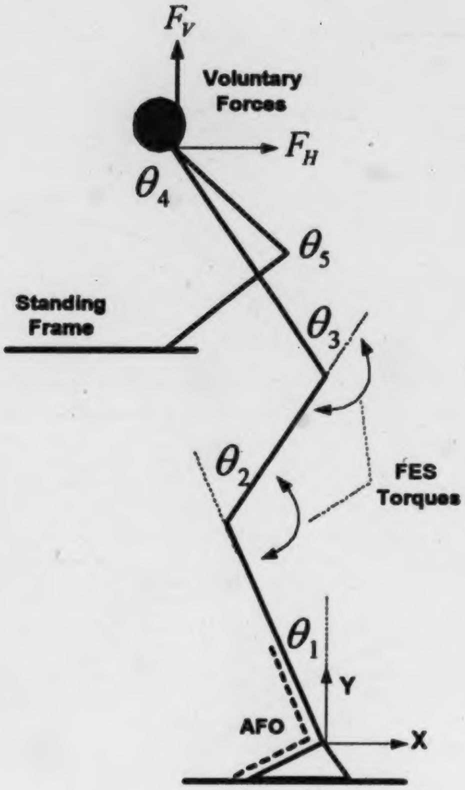
F_V
Voluntary Forces
F_H
θ_4
θ_5
Standing Frame
θ_3
θ_2
FES Torques
θ_1
Y
X
AFO

Figure 4.1 Body segmental model of the arm-assisted standing-up. θ_i's are the angular positions of the limbs measured relative to the previous limb (dashed lines). τ_i's are the net torques produced by the electrically stimulated muscles at the joints. F_H, F_v are the voluntary arm forces.

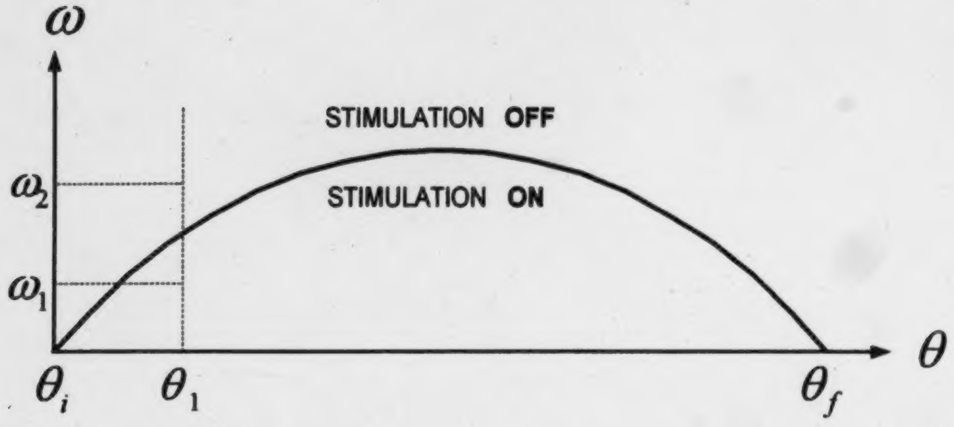
ω
STIMULATION OFF
STIMULATION ON
ω_2
ω_1
θ
θ_i
θ_1
θ_f

Figure 4.2 The switching curve used in SCURVE and PID control strategies. The switching curve represents the desired knee angular velocity (ω) versus the knee angle (θ). θ_i, θ_f are the knee angles at sitting and standing positions respectively.

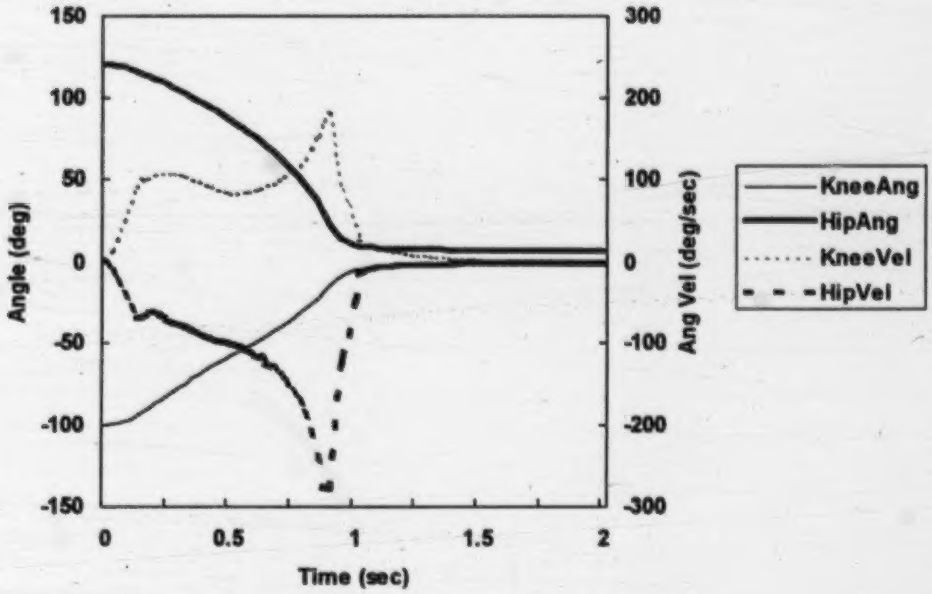

Figure 4.3 Typical joint trajectories for OPENMAX control of the knee extensors. Excessive electrical stimulation results in higher KEV but the maneuver completes in a shorter time.

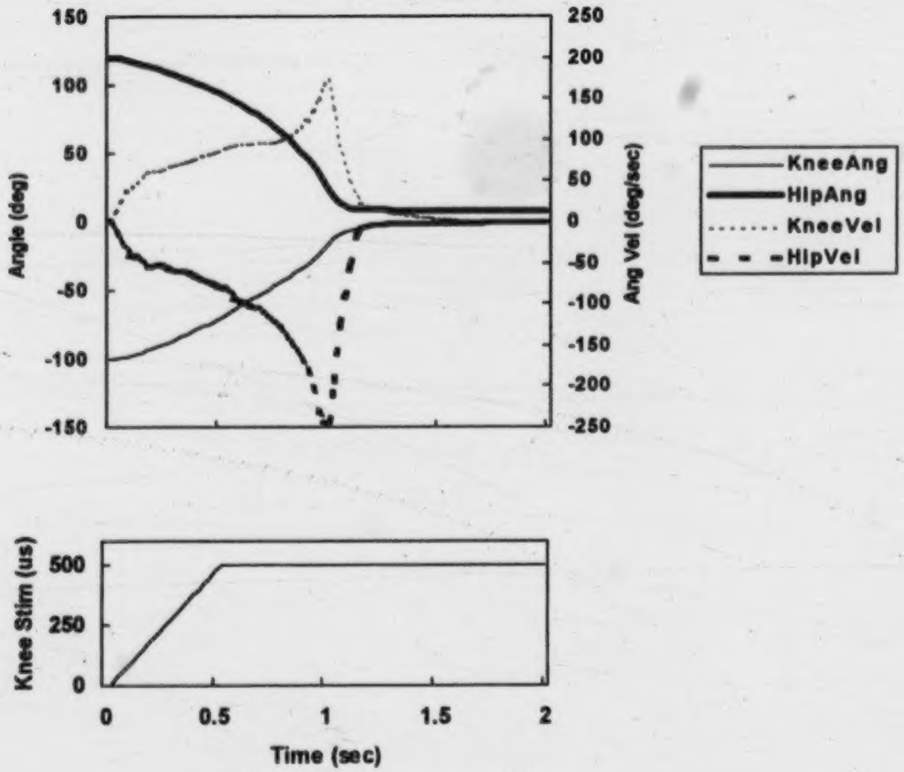

Figure 4.4 Typical joint trajectories for OPENLIN controls of the knee extensors. The gradual increase of stimulation at the initial phase results in higher arm force and longer time of maneuver but the terminal knee velocity is as high as OPENMAX.

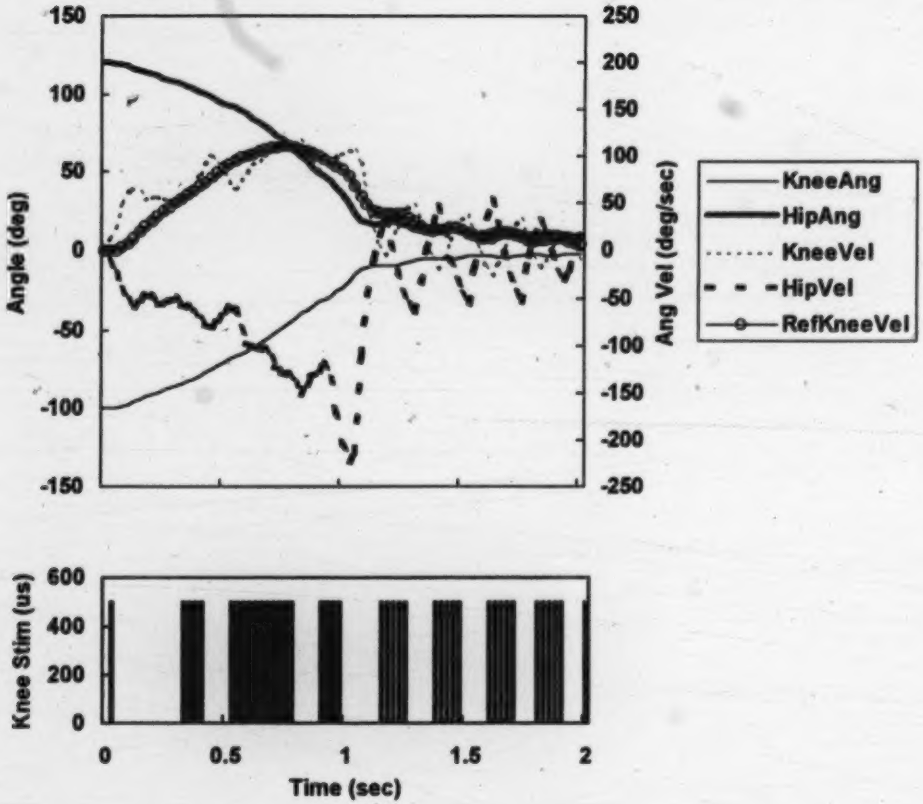

Figure 4.5 Typical joint trajectories for SCURVE control of the knee extensors. Compared to OPENMAX, the terminal knee velocity is reduced but time of the maneuver is longer, more arm force is required, trajectory is jerky and limit cycling is experienced in terminal phase of the maneuver.

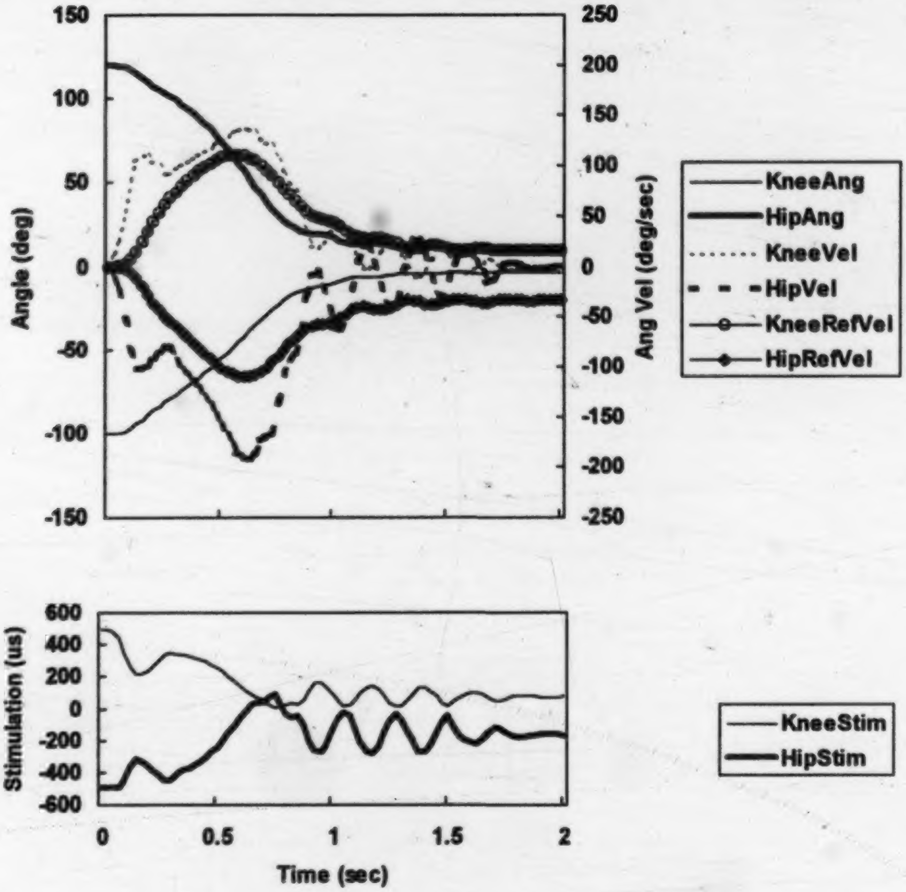

Figure 4.6 Typical joint trajectories for PID control of the knee and hip joints. Larger controller constants are needed to satisfy the requirements of the whole motion, which in turn results in oscillatory behavior at terminal phase.

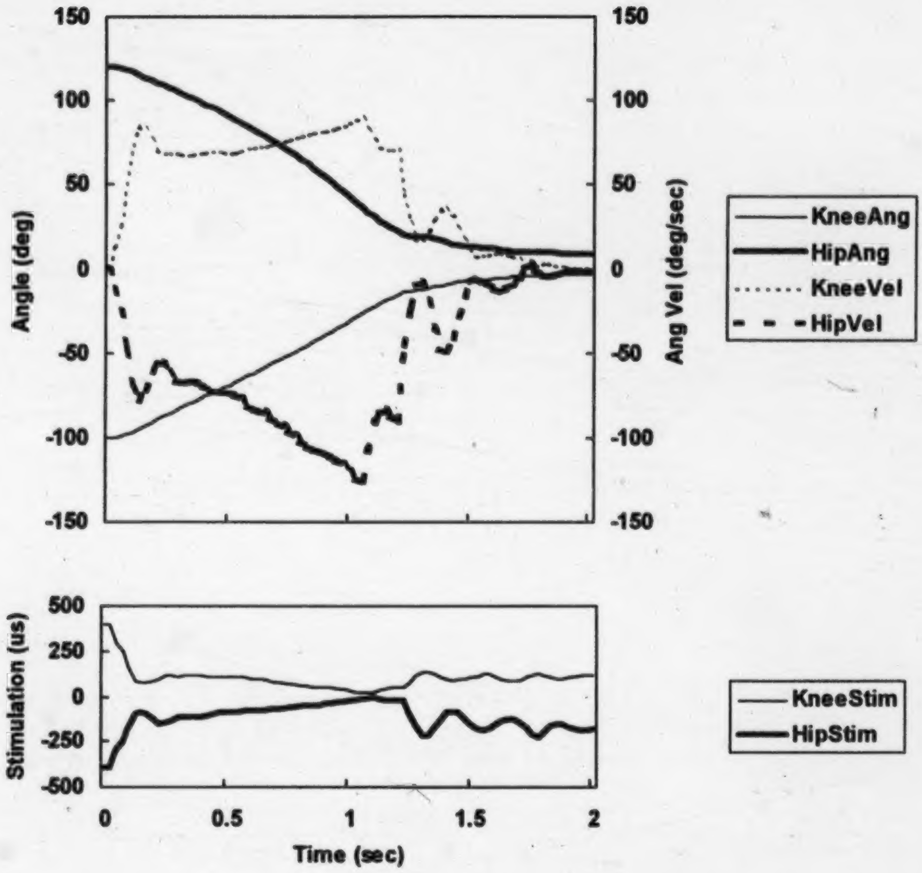

Figure 4.7 Typical joint trajectories for FUZZY control of the knee and hip joints. Too many parameters make FUZZY difficult to design but also make it flexible. The FUZZY controllers shown here result in lower terminal knee velocity and arm force than other closed-loop controllers.

Subject mass	70.0 kg
Subject height	1.75 m
Muscle fatigue time constant	105 sec
Muscle time constant	30 ms
Stimulation delay	50 ms
Initial Ankle angle	15°
Initial knee angle	-100°
Initial Hip angle	120°
Integration time step	0.005 sec
Maximum knee extensor torque	85.0 N.m
Maximum knee flexor torque	42.5 N.m
Maximum hip extensor torque	55.0 N.m
Maximum hip flexor torque	27.5 N.m

Table 4.1 Model parameters for simulation experiments.

Joints Stand-up strategy	Knee Joint Torque (N.m)	Hip Joint Torque (N.m)
Knee only stimulation	105	0
Hip only stimulation	0	148
Knee/Hip stimulation	65	55

Table 4.2 Minimal joint torque for FES standing-up with no vertical arm force.

Criteria **Strategy**	**Time of Standing-up (sec)**	**Average knee stimulation (μs)**	**Average arm force (N)**	**Terminal Knee velocity (°/sec)**
OPENMAX	1.2	500 (600)	133 (160)	178.7
OPENLIN	1.25	433 (541)	159 (199)	172.8
SCURVE	1.78	242 (431)	205 (365)	90.1
PID	1.32	248 (327)	185 (244)	63.5
FUZZY	1.45	211 (306)	143 (207)	53.7

Table 4.3 Performance of the different controllers applied to knee stimulation strategy. Total values of the stimulation (in $\mu s.S$) and arm forces (in $N.S$) are given in parentheses as measures of energy expenditure.

Criteria Strategy	Total time of standing-up (sec)	Average electrical stimulation (μs)	Average voluntary arm forces (N)	Terminal Knee velocity (°/sec)
OPENMAX	0.9	500 (900)	101 (91)	247.5
OPENLIN	1.05	398 (836)	121 (127)	238.6
SCURVE	1.50	148 (444)	179 (268)	110.8
PID	1.30	197 (512)	156 (203)	57.5
FUZZY	1.15	208 (478)	139 (160)	42.8

Table 4.4 Performance of the different controllers applied to the knee and hip stimulation strategy. Total values of the stimulation (in $\mu s.S$) and arm forces (in $N.S$) are given in parentheses as measures of energy expenditure.

5 Design of Optimal Controllers for FES-Assisted Standing-up using Genetic Algorithms

5.1 Introduction

Standing-up and being upright is a prerequisite for many of activities of daily life such as the initiation of walking, reaching down high objects, making transfers and face to face interactions with others. In addition to functional benefits, regular standing and weight-bearing may also provide important therapeutic benefits (Andrews and Wheeler, 1995; Kralj and Bajd, 1989).

The feasibility of FES assisted standing for paraplegics has been demonstrated (Kralj and Bajd, 1989; Andrews et al., 1988; Petrofsky et al., 1984). The open-loop procedure proposed by Kralj and Bajd (Kralj and Bajd, 1989) is still widely used clinically. The technique is straightforward and works well for many people. However, for some the terminal velocity reached during sitting-down may be potentially damaging to the insensate tissues of the buttocks. In some patients, considerable upper limb forces are required which may cause or exacerbate shoulder pain in this population where overuse syndrome is common (Bayley et al., 1987). Also cause for concern are the terminal velocities of the knee joint which are higher than normal and may be a cause for concern of joint damage.

A number of experimental closed-loop schemes have been suggested to solve these problems (Dolan et al., 1998; Ewins et al., 1988; Mulder et al., 1992). In these studies, the controller parameters were usually designed by trial and error. However, in our hands, manual tuning of the controller parameters is difficult because the dynamics of standing-up and sitting-down is nonlinear, has a high degree of inter-segmental coupling and is affected by the voluntary arm forces. In a previous study (Davoodi and Andrews, 1996b), the simple open-loop controls and the closed-loop on/off switching curve control were simple to design and it was possible to evaluate their capabilities by manual design. The PID and Fuzzy Logic controller of (Ewins et al., 1988; Davoodi and Andrews, 1996b), were more tedious to tune because of the increased number of parameters to tune.

Here we consider the sit-stand and standing phases of the maneuver, and demonstrate the feasibility, using computer simulation, of automatic tuning for PID and fuzzy controllers using a Genetic Algorithm (GA) based global optimization. We will also consider the more difficult situation in which, both the knee and hip joints were controlled simultaneously by FES. The objective of optimization is to minimize the upper limb forces, and reduce the terminal velocity of the knee. The open-loop maximal stimulation of the knee and hip joint extensors (an extension to the open-loop method introduced by Kralj and Bajd (Kralj and Bajd, 1989) to include hip joint extensors) will be used as a basis for comparison.

5.2 Methods

5.2.1 Computer Model of Paraplegic Standing-up

Biomechanics of the paraplegic standing-up is represented by a planar model in sagittal plane. The model is composed of four parts: body segmental model, muscle model, passive joint model and a model of voluntary arm forces. Body segmental model is composed of five segments, shank, thigh, trunk-head, upper arm and forearm that are connected via friction-less pin joints in a closed chain configuration. The knee and hip joints are driven by electrical stimulation of their extensors and flexors. The shank plantar flexion is limited by an ankle foot orthosis (AFO). The mass center of each segment lies in the line connecting the two adjacent joints. Anthropometric data are obtained from (Winter, 1990) and scaled to the total body mass and height. The torque actions of the extensor and flexor muscles in response to the electrical stimulation are modeled by first-order dynamics including static nonlinearities, time delays and fatigue models. The torque exerted by the passive joint structure has two components, elastic and damping torque. Sum of two exponentials is used to model the elastic component. The damping torque across the joint is modeled with a linear function of the joint velocity. The overall arm force actions are represented by a horizontal and a vertical force acting on the shoulder joint. The voluntary control of these forces is modeled by handcrafted Fuzzy Logic controllers. Details of the model development and its validation can be found in (Davoodi and Andrews, 1996a).

5.2.2 Genetic Algorithms Optimization Method

Genetic algorithms are optimization procedures that are based on the mechanics of natural selection and genetics to produce increasingly fitter populations (Goldberg, 1989). They start with a population of randomly chosen chromosomes and evolve toward higher fitness by applying genetic operators such as reproduction, crossover and mutation.

A chromosome, is a candidate solution, for example, it can be a binary coded string of all the design variables (Figure 5.1.A). Reproduction produces a new generation where chromosomes with higher fitness have better chance for further reproduction. Crossover results in randomized, yet structured information exchange between chromosomes to produce new patterns while mutation maintains diversity (Figure 5.1 .B and C). This reproductive cycle is called evolution and continues until optimization of an objective function is achieved.

In contrast to other optimization methods, GA only uses the value of the objective function and therefore, the function does not need to be continuous and differentiable. They can work with various types of variables at the same time as long as they can be encoded in a binary string. Instead of a single point, they simultaneously operate on a group of points within the search space. This increases efficiency in searching large spaces and robustness in finding global optimum of multi-modal functions (Goldberg, 1989).

To synthesize controllers for paraplegic standing-up, we consider the musculoskeletal dynamics and the voluntary arm forces as part of overall optimization task in which the GA automatically tunes the controller's parameters.

5.2.3 Selection of the Tuning Parameters

The tuning parameters for PID control are the proportional, derivative and integral constants. Two parallel PID controllers are used for the knee and hip joints i.e., 6 parameters to tune. However, as shown in (Ewins et al., 1988; Davoodi and Andrews, 1996b), one set of PID controller parameters is insufficient to accommodate the sit-stand transition and to maintain standing. Here, we use gain scheduling PID controllers in which each controller parameter is a piece-wise linear function of joint angle. The joint angle space was subdivided into three regions each with a linear function defined to represent the value of the controller constant within that region (Figure 5.2). The shape of the function will depend on the values of the four controller constants at the borders of the three regions. These four values were selected as the tuning parameters. Since there are three constants for each controller and two controllers, 24 tuning parameters must be optimized by the GA.

The fuzzy controllers described in (Davoodi and Andrews, 1996b) have two inputs, each represented by 6 triangular fuzzy membership functions and one output represented by 36 singleton fuzzy membership functions (Cox, 1994). The input membership functions were fixed and the output singletons were the tuning variables i.e. 36 parameters for each controller which resulted in 72 tuning parameters for two fuzzy controllers.

Eight-bit binary numbers were used to encode each tuning parameter resulting in chromosomes length of 192 and 576 bits for the PID and fuzzy controllers respectively.

5.2.4 Determination of the Fitness Function for GA Optimization

At each stage in the process of evolution, the GA attempted to maximize the fitness function for each candidate solution. In contrast, conventional optimization techniques minimize an objective function. Each measure can be obtained easily given the other one. For example, the fitness function is usually obtained by subtracting the objective function from a constant value that is higher than all the possible values of the objective function. The fitness of each solution is measured by criteria such as the smoothness of the trajectory and the total arm forces. These criteria are included in the fitness function.

There are other essential constraints e.g. the maneuver must be successful and finish within a reasonable time. These conditions were enforced by penalizing the fitness function. Any standing-up trial was considered a success if specific joint positions and velocities are reached before the maximum allowable time, otherwise, it is a failure that is punished by assigning a zero fitness value. Therefore, the GA performs two important tasks. It first finds successful trials by receiving only the failure/success signal from the system, and then optimizes certain performance criteria for the successful trials.

Since, multiple criteria must be optimized, a novel approach is used to directly construct the overall fitness function. First, measures representing the trajectory error, total stimulation, total arm forces were obtained for *n* chromosomes in the population.

$$J_{traj}(i) = \sum_{sit}^{stand} (\omega_k(i) - \omega_{kd}(i))^2 + (\omega_h(i) - \omega_{hd}(i))^2 \qquad i = 1,2,\ldots n$$

$$J_{stim}(i) = \sum_{sit}^{stand} (S_k^2(i) + S_h^2(i)) \qquad i = 1,2,\ldots n$$

$$J_{vf}(i) = \sum_{sit}^{stand} (F_x^2(i) + F_y^2(i)) \qquad i = 1,2\ldots n \qquad (5.1)$$

Where, J_{traj}, J_{stim} *and* J_{vf} are the criteria representing the magnitude of the trajectory error, total electrical stimulation and total arm forces respectively.

ω_k and ω_h are the angular velocities and ω_{kd} and ω_{hd} are the desired angular velocities of the knee and hip joints respectively.

S_k and S_h are the electrical stimulation applied to the knee and hip joints.

F_x and F_y are the horizontal and vertical components of the voluntary arm forces applied at the shoulder joint.

The three arrays formed for the individual criterion was ranked according to integer numbers raging from *1* to *n*. For example an array element with the highest value would be ranked *1* and the element with the lowest value would be ranked *n*. As the result all the criteria are now in the same scale, i.e., *1* to *n*.

Finally, the overall fitness function can be directly formed by the weighted sum of the ranked arrays, i.e.,

$$Fitness(i) = W_{traj}J_{traj}(i) + W_{stim}J_{stim}(i) + W_{vf}J_{vf}(i) \qquad i = 1,2,\ldots n \qquad (5.2)$$

Where, $W_{traj}, W_{stim}\ and\ W_{vf}$ are the weightings for the individual criteria. Weighting of zero eliminates the criterion from the fitness function. Equal weightings attribute equal importance to the criteria and the importance of each criterion can be changed by modifying its weighting relative to the others.

Fitness is the fitness function.

The fitness function as the result, will have higher values for the solutions with lower values for the criteria, i.e., its maximization is equivalent to the minimization of the criteria.

The GA optimization procedure was written using the C programming language and compiled with other components of the simulation program described in (Davoodi and Andrews, 1996b).

5.3 Simulation Results

5.3.1 Validation of the GA Optimization Method

These experiments were conducted to validate the GA for FES standing-up. To test the performance of the GA on optimization of difficult problems, the GA was used to optimize test mathematical functions with known results. The test functions were chosen from (Goldberg, 1989) that covers a wide range of possible optimization problems. The GA was successful and robust in optimizing the different test functions. However, because of space, only one will be included here which is a multi-dimensional version of $F(x)=x^2$ defined as:

$$F(x_1,x_2,....x_{40})=\sum_{i=1}^{40}x_i^2 \qquad 0\le x_i\le 256 \qquad (5.3)$$

It has a known minimum of zero at $x_1=x_2=.....x_{40}=0$.

As the result of using the GA optimization, F was reduced from 541035 in the first generation to 849 in the 100th generation. All the optimized variables were between 0 and 10 (mean=3.675). The number of the generations to obtain zero for all the variables was 432. In repeated trials, the search was always successful in finding the known result although slightly different number of generations was required each time.

To validate the GA optimization algorithms for the design of FES controllers, FUZZY controllers were tuned to minimize the total stimulation during standing-up. In order to test the robustness of the optimization algorithms and the generality of the optimal solutions, the experiment was repeated three times. All three optimization experiments managed to find similar solutions although each started from different regions of the search space. The trends of the total stimulation for the repeated trials are shown in Figure 5.3. The similarity of the final solution in repeated trials shows that the solution is most probably the global optimum.

5.3.2 Open-Loop Control of the Knee and Hip Joints

This is an extension of the open-loop strategy of Kralj and Bajd (Kralj and Bajd, 1989) who applied sub-maximal stimulation only to the knee extensors. We maximally stimulated both the knee and hip extensors. The resulting motion is shown in Figure 5.4. The average electrical stimulation pulsewidth to the joints was 500 μs. The average arm force was 101 N and the knee end velocity was 247.5 °/sec. This will provide a basis for the comparison of the PID and fuzzy controllers designed by the GA.

5.3.3 Optimal Gain-Scheduling PID Controllers

Two simulation experiments were performed to optimize the parameters of the knee and hip joint PID controllers. The objective of the first experiment (PID1) was for the knee and hip joints to follow the predefined reference trajectories similar to those of the normal subjects in order to achieve a smooth sit-stand transition. In fitness function, all the weightings were set to zero except for W_{ve} that was set to one. The reference angular velocity trajectory was a second order polynomial representing the joint angular velocity versus the joint angle as described in chapter 4. The PID controllers after 15 generations of GA optimization are shown in Figure 5.5. The trajectories are followed closely with average velocity error of 11.6 °/sec resulting in relatively smooth trajectories with knee end velocity as low as 11.2 °/sec. Compared to the open-loop strategy, the average arm force was 107% higher at 209 N but the average electrical stimulation was 70% lower at 151 μs.

In the second experiment (PID2), the objective was to minimize the arm forces. All the weightings in the fitness function were set to zero except for W_{af} that was set to one. As the result the average velocity error was 23.4 °/sec but the transition was still smooth with low knee end velocity of 45.4 °/sec. Compared to the open-loop strategy, the average arm force was only 31% higher at 132 N but the average electrical stimulation was 66% lower at 172 μs. The results are given in Table 5.1 for comparison.

5.3.4 Optimal Fuzzy Logic Controllers

Three optimization experiments were carried out to minimize the trajectory errors (FUZZY1), to minimize the arm forces (FUZZY2) and to minimize the combination of these two criteria (FUZZY3). Table 5.1 compares the results with those of the PID and open-loop controllers. The performance of the FUZZY1 is illustrated in Figure 5.6.

When minimizing the trajectory error, the trajectories were followed closely resulting in the average velocity error of 9.2 °/sec and the knee end velocity as low as 8.6 °/sec. Despite the improved trajectory control, the arm force was higher than the open-loop control by 135% but stimulation was lower by 72%. The minimization of the arm forces reduced them to a level very close to that of the open-loop control with only 14% higher average arm force while reducing the average stimulation by 59%. Combining the two criteria resulted in a compromise between the two so that both the velocity error and arm force were reduced but not to the level obtained in the first two optimization experiments.

5.3.5 Sensitivity Analysis of the Optimal Controllers

The robustness and sensitivity to model-subject mismatch and other disturbances was investigated. Because of redundancy in the arm forces and actuators, the robustness was high. However, the optimized performance may not remain optimal in the face of the changes in the parameter values.

We determined the change in the performance of the two selected optimal controllers (PID2 and FUZZY2 in Table 5.1) due to the model-subject mismatch. These optimal controllers were the ones designed to minimize the arm forces. The model parameters and initial conditions were changed ± 5% where possible and the resulting changes in the required arm force were obtained. The degradation in performance due to the change in parameter values is summarized in Table 5.2.

5.4 Discussion

FES assisted standing-up involves a complex musculoskeletal system that must be controlled by an active voluntary control of the upper body and the artificial FES controllers of the paralyzed muscles. Our objective was to find a purposeful coordination between the two controllers in which the two controllers follow similar objectives such as successful standing-up with smooth trajectories and minimal arm forces. This was achieved by optimization of the standing-up maneuver using GA global optimization method.

5.4.1 Validation of the GA Optimization Method

Validation experiments proved that the GA is a proper optimization method for our problem. It was always successful in finding the optimal solution for problems with high number of tuning parameters. Whether or not the optimal solution is global can always be questioned specially for the GA designed FES controllers where, the answers are not known beforehand and there is no 'gold standard' for verification since the problem does not lend itself to analysis by the conventional optimization methods. However, the GA initializes its first generation with random numbers, which means that the search starts from different regions of the search space. Obtaining similar results in repeated trials of the controller design experiments in Figure 5.3 shows that the results are most probably global.

5.4.2 Optimal Gain-Scheduling PID Controllers

The gain-scheduling PID (GS-PID) controllers had 24 parameters that were difficult to tune manually. The GA was able to tune these parameters so that the desired joint trajectories could be followed effectively. The GS-PID smoothly followed the sit-stand reference trajectories with near zero knee end velocity (KEV). This was in contrast to the simple fixed parameter PID controller shown in Figure 5.7. For example when using a fixed parameter PID, undesirable oscillation of the knee can be observed during the terminal phase of standing-up as illustrated in Figure 5.7. Because the parameters of this simple PID controller were manually tuned for smooth joint trajectories, higher arm forces were observed than would have been the case if the controller had been tuned to minimize arm forces. The second optimization experiment however, minimizes the arm forces for the given trajectories, i.e., it reduces the arm forces as much as possible while following the trajectories. The optimization therefore was a compromise between following the trajectories and reducing the arm forces which resulted in a considerable reduction in the arm forces to a level that was only 31% higher than the open-loop control. The arm forces although reduced were still higher than the open-loop control. This is the cost for achieving smoother trajectories. In other word, we can not reduce the arm forces to the amount required in open-loop control as long as the controlled joint velocities are desired.

The optimal PID controller constants in Figure 5.2 showed that for the PID control to be effective during the whole range of motion, the controller constants must be changed considerably. This again proved the results in the last chapter and in (Ewins et al., 1988) regarding the insufficiency of the single PID controller and the need for gain-scheduling PID controllers for this application.

5.4.3 Optimal Fuzzy Logic Controllers

The optimization objectives were similar to the gain-scheduling PID controllers, i.e., trajectory following and arm force reduction. In trajectory following experiment (FUZZY1 in Table 5.1), the resulting fuzzy controllers were able to follow the trajectories closely resulting in relatively smooth maneuver and low knee end velocity of 8.6 °/sec (Figure 5.6). The control of the joint velocities however resulted in increased arm force compared to the open-loop control although the stimulation was much lower (Table 5.1). Minimizing the arm forces was able to reduce them to a level only 14% higher than the open-loop control while the stimulation and knee end velocity were both reduced to less than half. Open-loop control in fact, applies the highest possible stimulation and therefore, results in the lowest arm forces. Excessive energy used in the open-loop control is wasted in the high terminal velocities that are also undesirable.

In FUZZY3 where two criteria with equal weightings are included in the fitness function, the moderate values of both performance criteria shows that the GA has made a compromise between the two criteria. Therefore, by the method used here it is possible to combine different criteria with their individual weightings.

5.4.4 Sensitivity and Robustness Analysis of Optimal Controllers

The changes in performance of the two optimal controllers, as a consequence of various model-subject mismatches, are shown in Table 5.2. The performance was least sensitive to the muscle force and initial joint positioning and most sensitive to the subject mass and height. In all cases the small mismatches resulted in small changes in the performance which means for the low model-subject mismatch the performance will remain near optimal. Therefore, it may be possible to design the optimal controllers using a computer model of the subject and then use it on the real subject without considerable degradation in the optimal performance.

In general, either the real subject or a dynamic model of the subject can be used to perform the standing-up trials for the GA. The required number of trials with present GAs are relatively high that makes it inconvenient if not impractical to use with the real subject. Therefore, we suggest a two stage design process that uses GA in stage one with a computer model of the subject to design an initial controller. In final stage, the initial controller can be applied to the subject and if it is not satisfactory, further fine-tuning can be performed using an on-line method.

The main idea is that if we use a dynamic model of the subject to design a controller, the closeness of the designed controller to the desired real controller resembles the closeness of the model to the real subject. This idea was tested by sensitivity analysis to the parameter errors that resembles the model-subject mismatch. It was shown that for small model-subject mismatch, the optimized controller remains near optimal. Therefore, it can be used as an initial controller that is globally optimal (or near optimal).

Finally, the optimization procedure proposed here, tunes the artificial FES controllers of the lower extremities to act in coordination with the voluntary control of the arm forces. In reality, the voluntary controller can also learn by interaction with the artificial controller. Here, we have ignored this capability because the modeling of the learning in voluntary control strategy is not presently possible. We think this problem requires further investigation. One possibility is to keep one of the controllers fixed and let the other to adapt itself. We used this approach by employing a stationary voluntary control strategy and having the GA to tune the parameters of the artificial FES controllers. The similar approach was used by Matjacic (Matjacic and Bajd, 1997) where he let the voluntary control of the paraplegic subject to adapt to the fixed FES strategy to maintain standing. A more comprehensive possibility is to let both of the controllers adapt by interacting with each other and the subject. Since the modeling of the learning behavior of the voluntary control is difficult, this configuration should be investigated in laboratory trials similar to those carried out by Matjacic (Matjacic and Bajd, 1997).

5.5 Conclusions

The results obtained in this study suggests that GA is a powerful optimization technique for the design of optimal controllers for FES standing-up. It designed controllers that were superior to the conventional open-loop controllers and manually designed closed-loop controllers. It was able to successfully coordinate the voluntary and artificial FES controllers to optimize certain performance criteria. A combination of the criteria could be used in the objective function and each criterion could be weighted according to its importance.

The optimal PID and FUZZY controllers were able to follow the desired joint trajectories resulting in smooth maneuvers. They were able to reduce the arm forces to a very low level but not less than the open-loop method. This was due to the requirement for lower joint velocities that limited the amount of possible reduction in the arm forces. The designed controllers were able to control both standing-up and maintain standing.

Using the present GA's the required number of trials is high and a dynamic model of the subject is suggested for initial controller design. It was shown that as long as the model-subject mismatch is low, the designed controller would remain near optimal when applied to the real subject.

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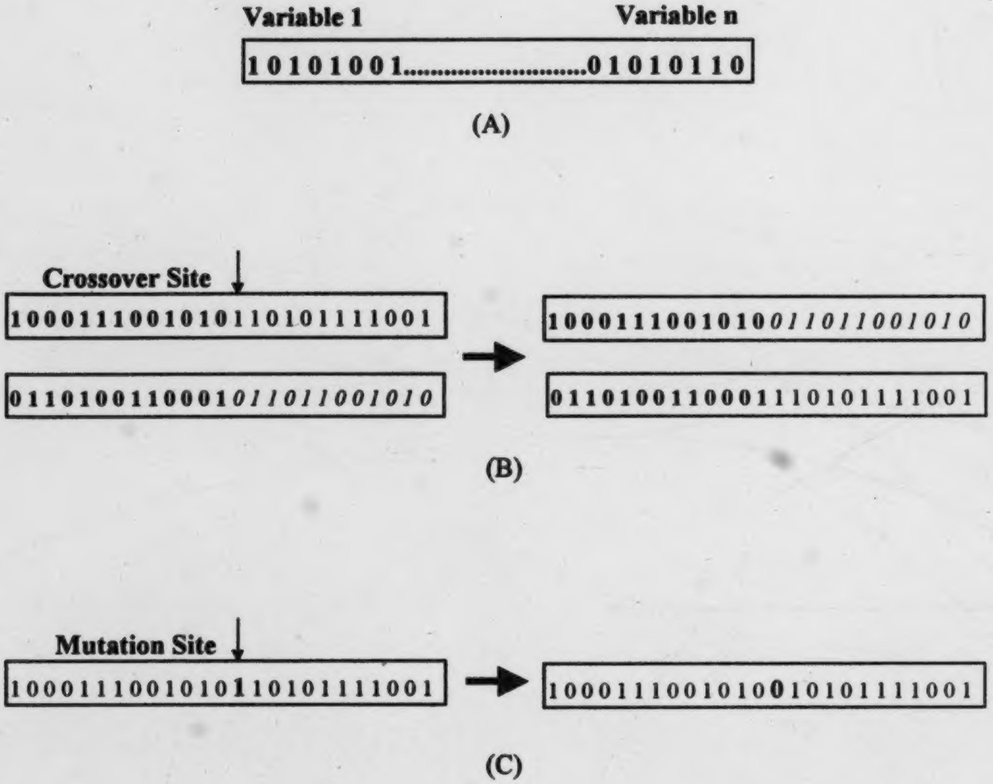
Variable 1
Variable n
10101001...........................01010110
(A)
Crossover Site
1000111001010110101111001
0110100110001011011001010
1000111001010011011001010
0110100110001110101111001
(B)
Mutation Site
1000111001010110101111001
1000111001010010101111001
(C)

Figure 5.1 Structure of the Genetic Algorithm optimization method. In (A) a chromosome is shown containing all the tuning variables coded into binary numbers. The crossover and mutation operations are demonstrated in (B) and (C). The chromosomes before and after operation are shown in the left and right respectively.

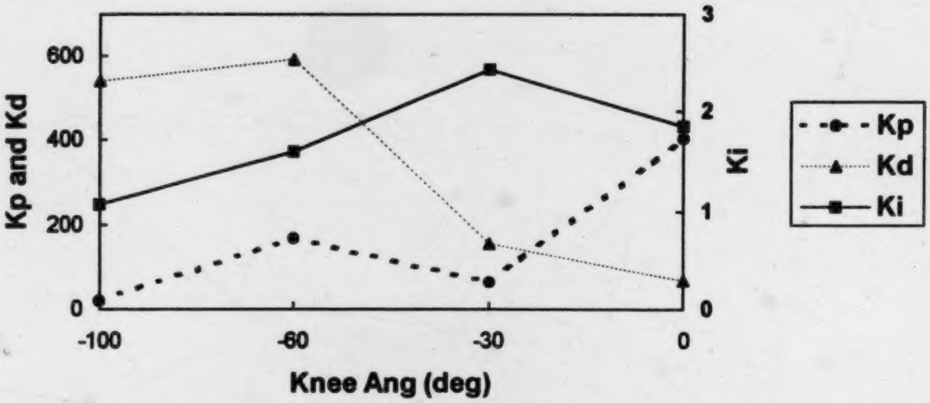

Figure 5.2 Constants of the PID controller optimized by the GA. Proportional (Kp, *μs/rad*), derivative (Kd, *μs.sec/rad*) and integral (Ki, *μs/rad/sec*) constants of the knee PID controller as functions of the knee joint angle. The results are from the optimization experiment to minimize the trajectory errors (PID1 in Table 5.1). The GA at four points optimized the values of the constants. The values in between the points are interpolated using three lines.

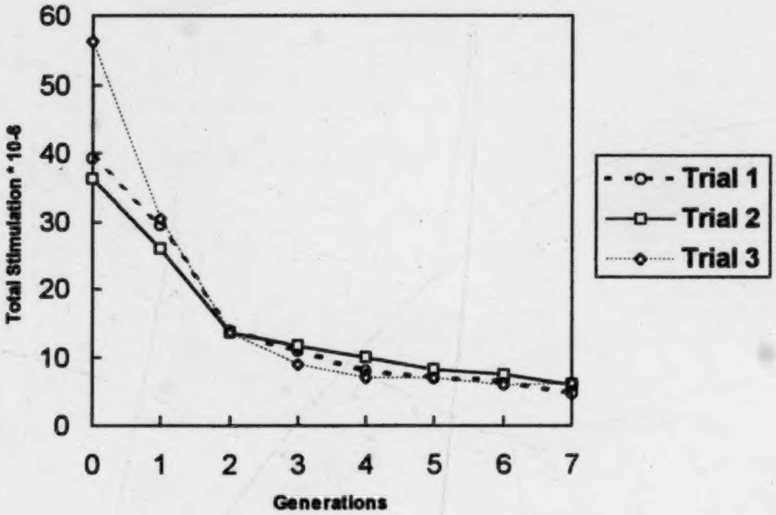

Figure 5.3 Performance of the GA optimization. The trends of the total stimulation vs. generations for repeated trials of the same controller design experiment are given. Starting from different regions of the search space, all three GA experiments converge to the similar solution, which is most probably the global minimum.

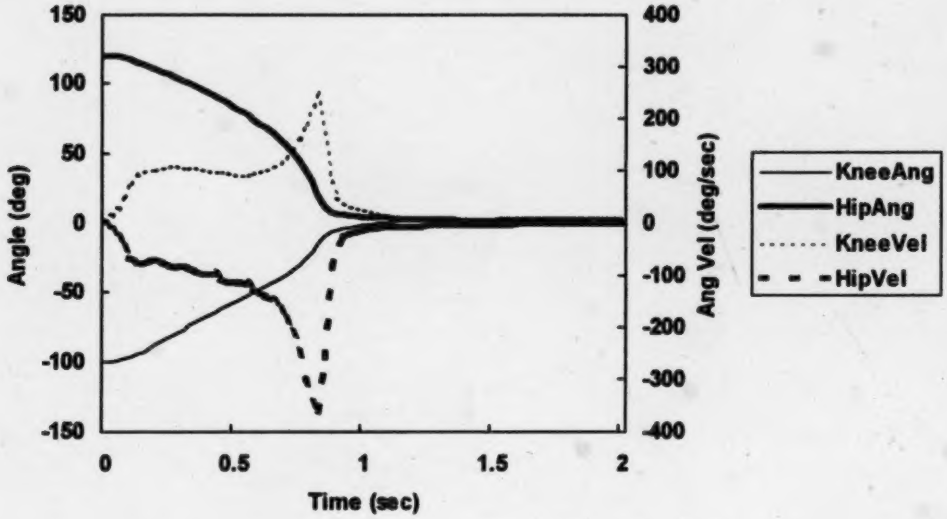

Figure 5.4 Typical joint trajectories for open-loop control of standing-up. Open-loop control maximally stimulates the knee and hip joint extensors. Excessive stimulation of the muscles results in the high knee end velocity.

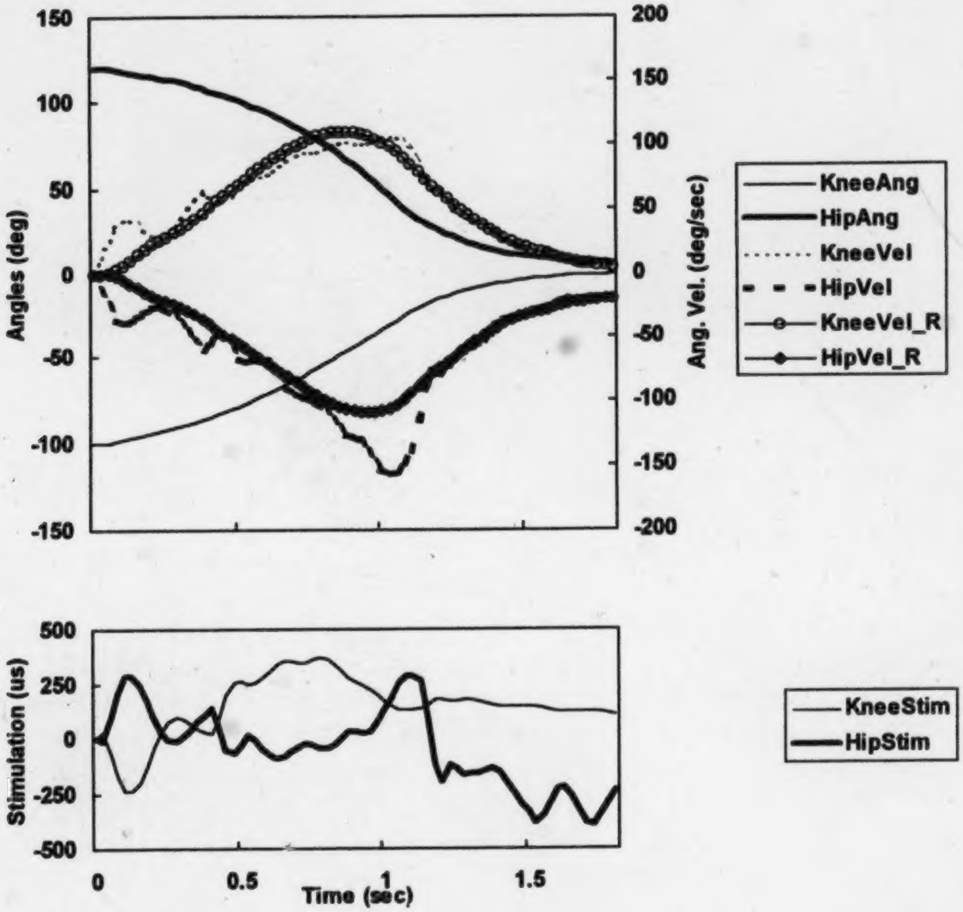

Figure 5.5 Performance of the PID1 controller optimized for trajectory following.

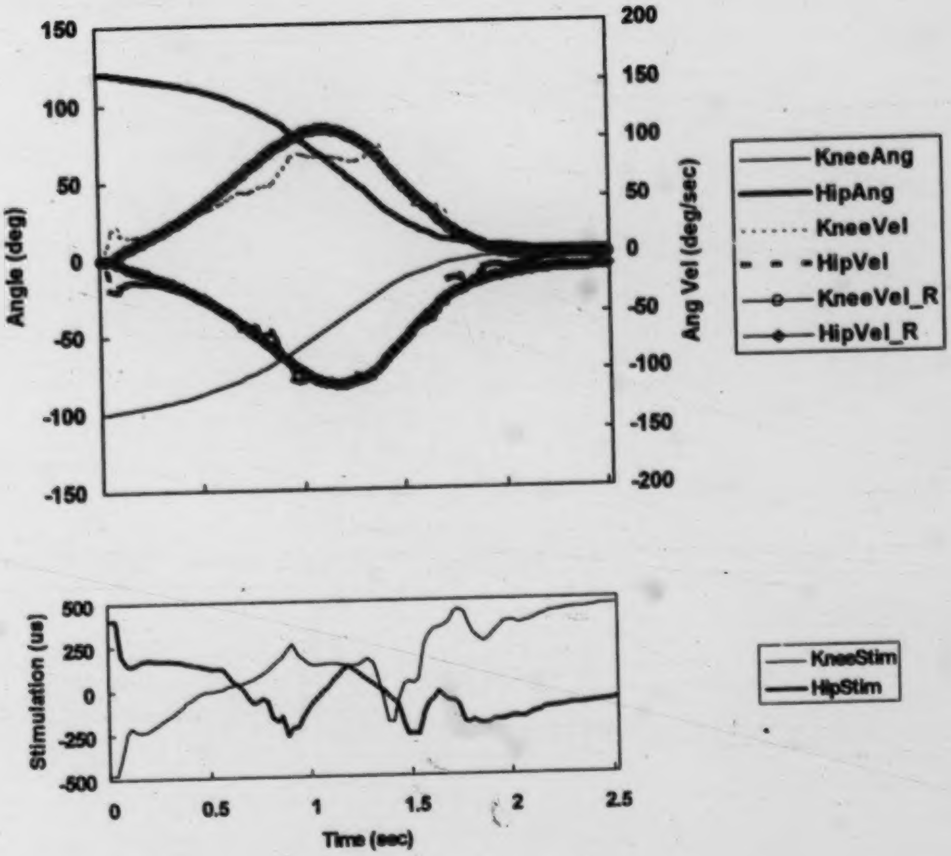

Figure 5.6 Performance of the FUZZY1 controller optimized for trajectory following.

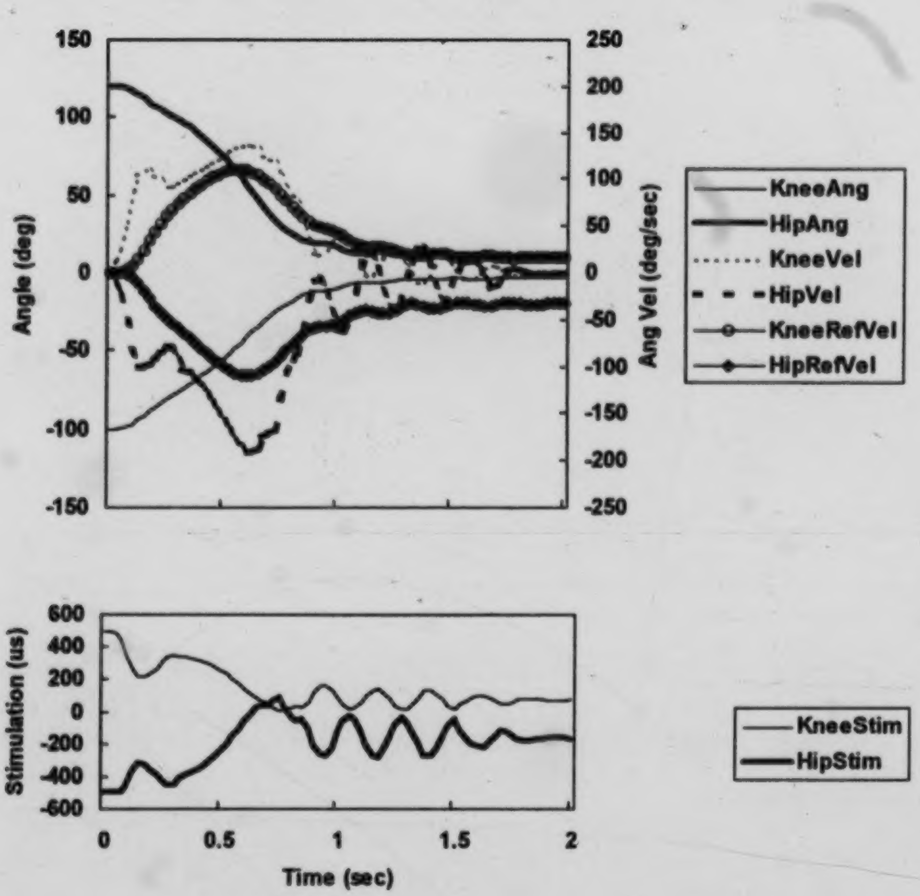

Figure 5.7 Typical simulation results for the control of the knee and hip joints using the standard PID control. Larger controller constants are needed to satisfy the requirements of the whole motion, which in turn results in oscillatory behavior at terminal phase.

Criteria Controllers	Total time of standing-up (sec)	Average electrical stimulation (μs)	Average arm force (N)	Average velocity Error (°/sec)	Knee end velocity (°/sec)
Open-loop	0.9	500 (900)	101 (91)	-	247.5
PID1 $W_{traj} = 1$	1.47	151 (444)	209 (307)	11.6	11.2
PID2 $W_{vf} = 1$	1.25	172 (429)	132 (165)	23.4	45.4
FUZZY1 $W_{traj} = 1$	1.72	138 (473)	237 (408)	9.2	8.6
FUZZY2 $W_{vf} = 1$	1.18	205 (485)	115 (136)	-	107.2
FUZZY3 $W_{traj} = 1$ $W_{vf} = 1$	1.62	234 (379)	157 (254)	21.3	48.6

Table 5.1 The performance of the GA optimized PID and Fuzzy controllers. The performance of the open-loop controller is given for comparison. Non-zero weightings in the fitness function are given. Total values of the stimulation (in $\mu s.S$) and arm forces (in $N.S$) are given in parentheses as measures of energy expenditure.

Parameters >>	Subject Mass		Subject height		Knee extensors		Initial Knee Angle	
	-5%	+5%	-2%	+2%	-5%	+5%	-5°	+5°
PID2 **Change in Avg. Arm Force (%)**	-5.9	+6.2	-2.3	+9.3	+0.7	-0.5	-1.6	+1.3
Fuzzy2 **Change in Avg. Arm Force (%)**	-8.6	+6.9	-1.1	+8.1	+0.9	-2.7	+1.83	+0.2

Table 5.2 Sensitivity analysis of the GA-designed PID2 and FUZZY2 controllers. The sensitivity of the average arm forces (minimized in both controllers) to the change in physical parameters and initial conditions are given.

6 Design of Self-Organizing Controllers for FES-Assisted Standing-up using Reinforcement Learning*

6.1 Introduction

Standing-up is a prerequisite for walking, reaching objects, transfers and face to face interaction with others. The regular use of functional electrical stimulation (FES) for standing may also provide important therapeutic benefits (Andrews and Wheeler, 1995; Daly et al., 1996; Graupe, 1994; Kralj and Bajd, 1989; Phillips, 1991). There is a requirement for improved FES control that requires a minimum of tuning or set up and can reduce upper limb effort and terminal knee velocities. In this paper we present preliminary results of a computer simulation to demonstrate the feasibility of robust and self-adaptive control using Reinforcement Learning (RL). RL has its origins in animal learning and is based on the commonsense notion that if an action is followed by a satisfactory outcome, then the tendency to produce that action should be strengthened i.e. reinforced.

Kralj and Bajd (Kralj and Bajd, 1989) proposed a procedure for paraplegic FES standing-up in which constant intensity stimulation produces knee extension moment that differ significantly from normal. Normally, high knee moment occur at seat lift-off that are progressively reduced resulting in knee angular velocities close to zero at full extension (Doorenbosch et al., 1994; Kelly et al., 1976). The technique has been widely adopted and works adequately for many people, however, it is a compromise that requires manual adjustment to minimize the terminal knee velocities and the upper limb forces. The latter

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have been estimated to be as high as two-third of the body weight (Dolan et al., 1997; Kamnik et al., 1997). The long term effects of repetitive high transient loading of the arm during activities such as transfers and wheeling have been implicated in the high incidence of overuse syndromes in the spinal injured population (Bayley et al., 1987; Chisholm, 1997). Therefore, it is reasonable to develop safer FES systems that would also minimize upper limb pain when standing-up for those with overuse syndromes. Reducing the upper limb force requirements may also extend the techniques to the frailer patient or those with impaired upper limb function. Higher than normal terminal knee velocities may also be cause for concern since it is not yet known if repetitive insults to the ligaments that abruptly limit knee hyperextension may eventually be damaging.

Khang & Zajac (Khang and Zajac, 1989a; Khang and Zajac, 1989b) used a linearized model of paraplegic standing, formulated about vertical set point, to design an output feedback control law for unassisted standing in which the upper body forces were considered to be external disturbances. The model was able to maintain standing and recover when disturbed or from an initial position halfway between sitting and standing, however, the sit-to-stand maneuver was not described. The optimization technique used to determine the control law was computationally demanding procedure and not suitable for practical application. Donaldson and Yu (Donaldson and Yu, 1996) proposed a controller for minimizing the handgrip reaction forces by referring them to the equivalent leg joint moments. Static equilibrium equations must be solved for the equivalent leg joint moments and inverse models of the muscle recruitment curves are required to find the appropriate muscle stimulation levels. Ewins et al. (Ewins et al., 1988) used PID type closed loop knee controllers for FES standing-up, smoother trajectories were observed, however, the terminal knee velocities and upper limb loading were not reported. Quintern (Quintern et al., 1989) proposed a combination of a closed-loop PID and an open-loop feedforward controller for paraplegic standing. The feedforward control signal was either a simple ramp-up or was calculated using a model of standing. They suggest that more attention must be given to Man-Machine synchronization to improve the quality of FES movements. The necessity of coordination between the artificial controller and the intact natural motor control has also been emphasized in a work by Hunt et al (Hunt et al.,

1997) and Munih et al (Munih et al., 1997) where they used linear quadratic Gaussian (LQG) controller to restore unassisted standing in paraplegia. Andrews (Andrews, 1990) and Mulder et al. (Mulder et al., 1992a; Mulder et al., 1992b) used closed-loop ON/OFF control based on a pre-determined phase plane switching curve of the desired knee velocity versus knee angle. Andrews used a bell shaped switching curve to turn ON or OFF stimulation by comparing the actual knee velocity and angle with the template. In comparison to the basic maximal stimulation of the knee extensors, considerable improvements were reported in decreasing the terminal velocity of the knee joint and the amount of stimulation but the sit-stand maneuver took longer and more arm force was required.

A Fuzzy Logic controller (FLC) for FES standing-up has been demonstrated, in computer simulation, by the authors to have improved performance, in terms of the trajectory smoothness, knee end velocity and the required arm forces, compared with either PID control or ON/OFF phase plane switching techniques (Davoodi and Andrews, 1996). However, the amount of manual tuning required to optimize the fuzzy controller precluded its practical application. We have also determined the feasibility of optimizing the parameters of the Fuzzy Logic controllers using a Genetic Algorithm (GA) optimization method. However, the large number of trials before convergence to the optimal solution (>600) and computational overhead of the present GA algorithms make them unsuitable for on-line tuning. This experience led us to consider a self-adaptive scheme that uses RL to tune the parameters of the fuzzy logic controllers, i.e., the FLC-RL.

In order to conduct preliminary investigations into the feasibility of FLC-RL we required a test environment that could be precisely repeated, particularly as this adaptive technique learns over several trials. We therefore chose to conduct our investigations using computer simulation on a biomechanical model. Using this model we have explored the potential for FLC-RL control in FES, in particular, arm assisted FES standing-up after spinal injury. In this chapter we present our preliminary results related to the following questions. Can RL be extended to problems with more than one controller and continuous states and action spaces in particular the application to FES control of standing-up? Can

RL manage the coordination of the artificial FES controllers with the voluntary upper body forces to achieve a common objective? Can RL recover from transient disturbances typical of those encountered in practical FES standing-up? Can RL accommodate system changes due to muscle fatigue or anthropometric differences between patients? Can RL provide safe control and self-adapt quickly enough, particularly in the start up phase, for FES applications? Can RL simultaneously minimize upper limb loading and the terminal velocity of the knee joints?

6.2 Methods

6.2.1 Computer model of paraplegic standing-up

The sagittal plane model incorporates body segments, muscles, passive joint properties and voluntary use of the upper limbs. The shank, thigh, trunk-head, upper arm and forearm are assumed to be connected by frictionless pin joints in a closed chain configuration. Segmental centers of mass are assumed to lie on the line connecting the two adjacent joints and the physical parameters were scaled to body mass and height according to Winter (Winter, 1990). The resultant knee and hip joint moments in response to stimulation intensity were modeled by first-order transfer functions that include: saturation, neural transmission delays and a model of FES induced muscle fatigue described in (Durfee and Dilorenzo, 1990). Stimulation intensity was varied between zero and maximum (constant current with pulse width varied between 0 to 500 μs) producing joint moment according to the sign convention of Figure 6.1. For example, if the knee joint controller output is positive stimulation is applied to the knee extensors and when negative to the knee flexors. The moment transmitted by the passive leg joint structures has both elastic and damping terms as described in (Mansour and Audu, 1986; Davy and Audu, 1987).

The voluntary upper body force actions were divided into active and passive parts. The active part consists of the activities of the arms musculature and is represented by equivalent forces at the shoulder joint (Figure 6.1). The passive part was achieved by leaving the arms in the model to provide the kinematic constraints and passive resistance. This was important to prevent the model from assuming impossible configurations. Linear springs and dampers were used to limit the range of movements of the shoulder and elbow joints to physiological limits. Both springs and dampers become effective when the joint angles reach the offset angles before the joint limits (Table 6.1). The horizontal and vertical components of the equivalent force at the shoulder joint were generated by fuzzy logic algorithms with the rules defined heuristically based on the assumption that these forces primarily provide balance and help in lifting the body. $\mathbf{F_X}$ moves the shoulder joint towards the center of the foot support area and is a function of the horizontal position and velocity of the shoulder joint. $\mathbf{F_Y}$ maintains a minimum upward speed and prevents downward movement of the shoulder joint and is a function of the vertical position and velocity of the shoulder joint. Unlike $\mathbf{F_X}$ and $\mathbf{F_Y}$ that could be related to clear objectives and the control rules could be defined heuristically, it was more difficult to do the same with $\mathbf{M_Z}$ and therefore it was not modeled. Five triangular membership functions were used for each input variable and seven for each output variable. The membership functions were all distributed evenly with 50% overlap over the domain of the variables. The set of rules for the fuzzy controllers of $\mathbf{F_X}$ and $\mathbf{F_Y}$ are given in Figure 6.2. The equations of motion were derived by applying D'Alembert-Lagrange principle (Paul, 1979; Wells, 1967; Roberson and Schwertassek, 1988). For the planar model in Figure 6.1 to be in general equilibrium the virtual power must vanish, i.e.,

$$\sum_{i=1}^{M}[(F_{xi}-m_i\ddot{x}_i)\dot{\tilde{x}}_i+(F_{yi}-m_i\ddot{y}_i)\dot{\tilde{y}}_i+(\tau_i-J_i\ddot{\theta}_i)\dot{\tilde{\theta}}_i]=0 \qquad (6.1)$$

Where, $M=5$ is the number of segments. m_i is the mass of the segment i, x_i and y_i are the coordinates of the center of mass of the segment i in an inertial reference frame, θ_i is the generalized coordinate for the segment i, $\tilde{x}_i, \tilde{y}_i$ *and* $\tilde{\theta}_i$ are the virtual displacements, F_{xi}, F_{yi} and τ_i are the external forces and moments applied to the center of mass of the segment i and J_i is the moment of inertia. about an axis passing the center of mass of the segment i perpendicular to the sagittal plane.

Application of (6.1) results in three equations of motion. For the closed chain system there are two additional constraint equations:

$$\sum_{i=1}^{M} l_i \cos(\theta_i) = v \quad \sum_{i=1}^{M} l_i \sin(\theta_i) = h \tag{6.2}$$

Where, l_i is the length of the segment i and v and h are the vertical and horizontal distances between the wrist and the ankle joints respectively. The equations of motion and the constraint equations must be solved for the angular accelerations, velocities and positions of the joints. In this study, the shank was fixed to simulate the effect of an ankle foot orthosis of the floor reaction type (Andrews et al., 1988). The model parameters for the simulation experiments are given in Table 6.1.

6.2.2 Development of the learning algorithms for the FLC-RL

The learning algorithms are combination of a procedure introduced by Sutton (Sutton, 1988), known as the temporal difference (TD) procedure and the reinforcement learning (RL) procedure (Barto et al., 1989). The combined algorithms can address the goal directed sequential decision making problems, traditionally solved by dynamic programming (Bellman and Kalaba, 1965; Ross, 1983) but do not require the model of the environment. The formal convergence proofs have only been obtained for the finite, stationary Markovian decision process (Sutton, 1988; Rummery and Niranjan, 1994; Watkins, 1989). Although most physical processes cannot strictly meet the formal conditions for applying these techniques, many researchers have been successful in applying them (Beom and Cho, 1995; Gullapalli, 1995; Howell et al., 1997; Ilg and Berns, 1995; Salatian et al., 1997; Yamaguchi et al., 1996).

Due to the changes in the body such as muscle fatigue, the problem posed here is not stationary. Further, the control actions and states are considered as continuous variables i.e. they can assume infinite number of values. It is our main objective however, to evaluate the performance of the RL and TD in the presence of these violations of the formal conditions.

Figure 6.3 illustrates the structure of the learning system. Two FLCs represent the knee and hip joint stimulation controllers and one FLC represents the value function. We call them knee FLC, hip FLC and value FLC. The value function *V(X)* estimates the value of state *X* and is defined as the sum of the future rewards when starting from state *X* and following a fixed control policy to the end of the trial. The structure of the FLC function approximator is shown in Figure 6.4. All the FLCs receive the partial state information including the knee and hip joint angular positions (more on this later in discussion):

$$X = [X_1, X_2] = [\textit{knee angle, hip angle}] \tag{6.3}$$

The outputs of the knee and hip FLCs are the stimulation pulsewidth of the respective joints S_k and S_h. The value FLC outputs the estimate of the value function V. Gaussian membership functions are used to encode the input variables. Central values of the membership functions were chosen for higher concentration in the sensitive regions such as the terminal phase of standing-up and the width values were chosen for approximately 50% overlap between the adjacent membership functions as depicted in Figure 6.5. The firing intensities of the fuzzy rules are calculated by applying the fuzzy multiplication "AND" operator as follows:

$$\varphi_l = AND(\mu_1, \mu_2) = \mu_1 . \mu_2 \tag{6.4}$$

Where, $l = 1,2,.....N$ is the rule number, φ_l is the firing rate of the rule l and μ_1 and μ_2 are the membership values of the rule's antecedents. The output of the FLCs (value FLC for example) then can be computed as:

$$V = \sum_{l=1}^{N} \varphi_l v_l \tag{6.5}$$

Where, v is the parameter vector of the value FLC. Similarly the parameter vectors for the knee and hip FLCs are k and h respectively.

The variability and exploration in the action selection policies (knee and hip joint controllers) are provided by the Random Search Unit (RSU in Figure 6.3) that adds random components to S_k and S_h. RSU generates random actions $S_k^{'}$ and $S_h^{'}$ with the mean values of S_k and S_h and a standard deviation that depends on the value estimate V as follows:

$$\sigma = \sigma_{\max}.(1 - \frac{1}{1+e^{-5V}}) \tag{6.6}$$

Here, σ is the standard deviation of the exploration and $\sigma_{\max}$ determines its maximum value. The standard deviation is higher when the value estimate is low therefore providing higher variability in actions to search for higher rewards. A higher value estimate is a sign that the optimal policy is approaching when the variability must be lowered to facilitate the convergence.

The objective of learning (parameter update box in Figure 6.3) is to adjust, in each time step, the parameter vectors of the knee, hip and value FLCs. In case of the value function for example, a general parameter estimation rule (Widrow and Stearns, 1985) can be used to correct its value:

$$v_{t+1} = v_t + \beta\, e_{t+1}\, \varphi_t \tag{6.7}$$

Where, e is the deviation of V from its true value, β is the learning rate and v and φ are the parameter and feature vectors from (6.5) respectively. The parameter update rule for v can be obtained by replacing e with TD error, $r_{t+1} + \gamma V_t(X_{t+1}) - V_t(X_t)$ and φ with eligibility trace $e_t^{v_i}$:

$$v_{t+1}^i = v_t^i + \beta_v\left[r_{t+1} + \gamma V_t(X_{t+1}) - V_t(X_t)\right]e_t^{v_i} \tag{6.8}$$

Here, β_v is the learning rate, $0 \le \gamma \le 1$ is the discount factor and r is the reward function that gives the immediate reward for taking an action a in state X. $e_t^{v_i}$ is the eligibility trace for parameter v defined using the following recursive equation:

$$e_{t+1}^{v_i} = \lambda_v e_t^{v_i} + \varphi_i \qquad 0 < \lambda_v < 1 \tag{6.9}$$

Where, λ_v is the exponential decaying factor. Equation (6.9) results in an exponentially decaying trace that attributes more importance to the recently activated nodes. The term "trace" refers to the ability of equation (6.9) to memorize a sequence of eligibilities (gradients here) from the past time steps. According to (6.9), the gradient φ_i of an activated node *i* at time *t* will leave a trace in the eligibility trace of that node in the future time steps that will exponentially fade away. Although different patterns can be used, the exponential pattern is more popular because it can be implemented recursively. By memorizing the current and past gradients or activated nodes, eligibility trace makes it possible to blame the current parameters for the current and past actions. This property is useful in time delay systems especially in FES systems with considerable neural transmission delay.

The parameters of the knee and hip FLCs are updated using a RL procedure. The RL algorithms for the knee and hip FLCs are similar, for example, the parameter update rule for the knee FLC is:

$$k^i_{t+1} = k^i_t + \beta_k\left[r_{t+1} + \gamma V_t(X_{t+1}) - V_t(X_t)\right]e^{k_i}_t \qquad (6.10)$$

Where, β_k is the learning rate and $e^{k_i}_t$ is the eligibility trace of the parameter k_i that is calculated using a recursive equation slightly different from (6.9):

$$e^{k_i}_{t+1} = \lambda_k e^{k_i}_t + \frac{\left(S'_k - S_k\right)}{\sigma}\varphi_i \qquad 0 < \lambda_k < 1 \qquad (6.11)$$

Here, λ_k is the exponential decaying factor. S_k and S'_k are the input and output of the RSU in Figure 6.3 and σ is the standard deviation of the exploration unit. Therefore, $(S'_k - S_k)/\sigma$ is the normalized perturbation added to the control actions, which along with the TD error determines how the parameters should be changed. For example if the positive perturbation results in higher state value (positive TD error) then it is desirable and the controller should be changed in the direction of the perturbation. On the other hand, if the resulting state value is lower, then the controller should be adjusted in the direction opposite to that of the perturbation.

6.2.3 Validating the learning algorithms

Formal mathematical proofs of convergence are presently only available for simple forms of RL (Sutton, 1988; Rummery and Niranjan, 1994; Watkins, 1989). The RL problem posed here is considerably different from the original RL problems, mainly because the states and actions are continuous and there are two controllers instead of one. The performance of the learning algorithms was evaluated by applying them to systems of increasing complexity. The first case was a system comprising a two dimensional double-integrator given by:

$$\begin{array}{ll} x(t)=x(t-1)+v_x(t)T+\tfrac{1}{2}a_x(t)T^2 & v_x(t)=v_x(t-1)+a_x(t)T \\ y(t)=y(t-1)+v_y(t)T+\tfrac{1}{2}a_y(t)T^2 & v_y(t)=v_y(t-1)+a_y(t)T \end{array} \qquad (6.12)$$

Where, $T = 0.025$ *Sec* is the sampling interval. x and y represent the position of a unit mass in a two-dimensional state space and v and a represent the velocity and acceleration respectively as indicated in Figure 6.6.a. Maximum velocities on each axis are limited to 2 m/s. If these limits are attained, further acceleration will maintain the original velocities. Two FLCs are used to control a_x and a_y to move the unit mass from the initial state **I** to the goal state **G**. A third FLC represents the value function. The inputs to the FLCs are the x and y coordinates of the unit mass. Each trial starts at state **I** and ends whenever the mass touches the right or down limits ($r=-1$), times out in 5 *sec* ($r=-1$) or reaches the 0.1 meter neighborhood of the goal state where the reward depends on the time t spent on transit:

$$r = 1 - 2t/t_{\max} \qquad (6.13)$$

Here, $t_{\max}$ is the maximum time allowed for each trial equal to 5 *sec*. The reward is zero on all the other time steps. The mass can not penetrate the left or up limits. The objective of learning is to reach the goal state as quickly as possible. The convergence was assumed if the total time in the last 10 consecutive successful trials had not varied by more than 0.1 *sec*. Successful trials were those that ended in the goal state. By trial and error, a set of learning parameters ($\sigma_{\max}=0.1$, $\gamma=0.9$, $\lambda_v=\lambda_x=\lambda_y=0.95$, $\beta_v=0.1$

and $\beta_x = \beta_y = 0.001$) was found that resulted in convergence of the learning algorithms. These values were used in all the learning simulations on the double integrator problem.

The average number of trials for convergence in 10 consecutive simulations was 154 (ranging from 75 to 224). For a learning experiment that took 95 trials to converge, various trajectories corresponding to the different stages of learning and the learning rate are shown in Figure 6.6.a and b respectively.

To evaluate the effect on learning efficiency of typical complexities seen in FES systems the above simple double-integrator system was modified to include coupling between the two degrees of freedom and gravitational terms. Before applying to the unit mass, the outputs of the two controllers (a_x and a_y) were modified as follows:

$$\begin{aligned} a_x &= a_x + C_y a_y + G_x \\ a_y &= a_y + C_x a_x + G_y \end{aligned} \qquad (6.14)$$

Where, G_x and G_y were the x and y components of the gravitational force. C_x and C_y were the coupling indices representing how the acceleration in one axis affects the acceleration on the other axis. Positive G_x and negative G_y tends to move the unit mass in Figure 6.6.a toward **I** and away from the goal state **G**. This is similar to the effect of the gravity in moving the subject toward the sitting position and away from the goal state which is the standing position. Coupling indices represent the effects that each joint's motion has on the others and depending on the configuration could be negative or positive. Although the gravitational forces and the coupling indices in standing-up have more complex forms, only constant values of C and G are simulated here for simplicity.

When only coupling was implemented, the performance depended on the sign of the coupling indices. For example in 10 consecutive simulations, with $C_x = C_y = 0.1$, the average number of trials required to reach convergence increased to 178 (range 60 to 493). Whereas with $C_x = C_y = -0.1$ the average number of trials required for convergence decreased to 93 (range 37 to 150).

The addition of the gravitational term always degraded the learning rate because it tends to move the mass away from the goal state. For example, setting the gravity terms to $G_x = -G_y = 2\,m/s^2$ and $G_x = -G_y = 3\,m/s^2$ on average required 189 and 332 trials for convergence respectively.

6.2.4 Computer Implementation

The model of the voluntary arm forces was developed using Matlab's Fuzzy Logic Toolbox (The MathWorks Inc., USA) and then exported to a C program. The equations of motion, the three FLCs of the learning system and the RL algorithms were all programmed in C. These programs along with the C code of the voluntary arm forces were implemented in the LabWindows/CVI environment (National Instrument, USA). The latter provides the investigator with a useful "virtual Instrument Panel" for changing the simulation parameters. 4th-order variable step Runge-Kutta numerical integration method was used to integrate the equations of motion. A 3D animation facility was also developed to help in visualizing the simulated motions.

6.3 Simulation Results

6.3.1 Applying the FLC-RL to the control of standing-up

In addition to complications such as couplings and gravitational effects, the dynamics of arm-assisted standing-up in paraplegia is highly nonlinear and there are neural transmission delays associated with the muscle actuators. Furthermore, control actions that may compromise patient safety are unacceptable and a large number of learning trials to reach a solution would be impractical. In arm-assisted standing-up, the arms are used for balance and body weight support regardless of the FES control strategy. The role of the RL could be to learn control strategies that would improve the quality of standing-up. For example, by reducing the required arm forces or reducing the terminal velocity of the knee joint. The following simulation experiments explore such possibilities. The learning parameters for the following simulations were $\sigma_{\max} = 0.15$, $\gamma = 0.9$, $\lambda_v = \lambda_k = \lambda_h = 0.95$, $\beta_v = 0.1$ and $\beta_k = \beta_h = 0.0025$.

6.3.2 Learning to compensate for weak arm forces.

The maximum value of the vertical arm force $\mathbf{F_Y}$ was usually assumed to equal the subject's weight. However, in this simulation, this maximum was reduced to 76% of body weight so that the subject was unable to stand-up as depicted in Figure 6.7 by the dashed lines. Starting with this setting the goal of the FLC-RL was to find FES controllers for the knee and hip joints that were successful in standing-up. Standing-up was considered as successful when the absolute values of the knee and hip joint angles were less that 5° and the absolute value of the knee and hip joint velocities were less that 5 °/sec. The reward was always zero except for the end of trial (failure, timeout or reaching to standing position) where it was defined as $r = 1 - 2d / d_{\max}$. Here, d is the Euclidean distance between the end state and the standing position and $d_{\max}$ is the highest possible value of d in the state space. By this definition, the control actions that moved the subject closer to the standing position were rewarded, the closer the end state was to the standing position, the higher the reward. Convergence was assumed when the last 10 trials all successfully ended in the standing position. Convergence was achieved in 29 trials and Figure 6.7 shows the performance of the FES controllers at different stages of learning.

6.3.3 Learning to minimize arm forces

At the start of the learning phase, the model subject was forced to use only her arms to stand-up because the stimulus intensity outputs of the FES controllers were set to zero (the weights of the FLCs were initially set to zero). The control actions leading to failure, i.e. not being able to assume standing position within 4 *sec* were punished by setting $r = -1$. During standing-up, the reward for all other time steps was zero except for successful trials where the reward was inversely related to the integral of the arm forces. Therefore, to maximize its reward, the FLC-RL must learn control strategies for the knee and hip joints that reduce the arm forces. The integral of the arm forces was used as a convenient measure representing, approximately, the energy expended by the musculature of the upper body. Convergence was assumed if the last 10 trials were all successful and during these 10 trials, the integral of the arm forces did not change by more than 1% of the maximum value of the integral. The maximum value of the integral corresponds to the case where no FES is used to assist standing-up i.e. when maximum arm force is used.

The learning converged after 276 trials and the FES control strategies at different stages of learning are shown in Figure 6.8. The FLC-RL controller was able to reduce the total arm force by 78% compared to the case of arm only standing-up.

6.3.4 Learning to minimize the terminal velocity of the knee and arm forces simultaneously

Reducing both arm forces and the knee end velocity was achieved as follows. Instead of setting the initial controller weights to zero, we set them to produce the maximum stimulus intensity everywhere in the state space (this can be easily achieved by setting all the weights to a constant value) causing the knee end velocity to be high and the arm forces to be low. To reduce the knee end velocity, the control actions leading to successful trials were rewarded inversely with the magnitude of the knee end velocity. The reward was -1 for failure or timeout and zero at all other time steps. Convergence was assumed if the last 10 trials were successful and the knee end velocity in these trials did not change by more than 1 °/sec.

Unlike, the previous learning experiments, the convergence here was more sensitive to the learning parameters. Even for the fixed set of the learning parameters, not all the simulations converged to a solution. Figure 6.9 shows one of the successful simulations that converged in 238 trials.

6.3.5 Effects of system changes and disturbances

The optimal fuzzy logic controllers that minimized the arm forces were robust to sudden changes (duration 200 ms in the middle of the sit-stand maneuver) of more than ±100%

in the arm forces or the knee joint strength due to the spasticity. Like any other adaptive system, RL can not adapt to these kinds of sudden disturbances with no regular pattern or association to the state of the system.

The RL can adapt to the sustained disturbances with sudden onset. For example, when an optimized controller is trained on a model subject then switched to another subject with significantly different physical parameters. The adaptation of the RL to the permanent changes in the system parameters was typically much faster than the initial learning. In the experiment to compensate for the weak arm forces, it took 29 learning trials to tune the controllers so that they could reliably perform successful standing-up maneuvers. At this point, we increased the subject's mass by 10% whilst learning was in progress. As a result the controller failed to perform standing-up successfully, however, it took only 7 additional trials to recover and perform satisfactorily thereafter. Similarly when we increased the subject's mass by 14% it took 11 additional learning trials to recover. As another example, the learning to minimize the arm forces was converged in 276 trials. At this point we increased the subjects' mass by 5% whilst learning was in progress. The learning was converged in only 11 additional trials. Increase of another 5% to the mass at this point, required another 13 trials to converge.

6.4 Discussion

6.4.1 Validating the RL algorithms

At the time of writing the authors are unaware of any formal proofs of convergence for a problem with more than one controller and continuous state and action spaces. However, our RL algorithm converged in all simulations involving the double integrator test system even when coupling and gravitational factors similar to those found in the dynamics of FES standing-up were included. However, the learning rate became slower with the increased complexity.

6.4.2 Applying RL to the control of standing-up

In our modeling we have assumed that the use of the arms would avoid falling and that the RL would intervene to improve some measures of the reinforcement signal. In general for RL problems, failure constitutes an important part of the learning process since it is always possible to find the goal state by visiting all the failure states and avoiding them. However, we chose to constrain the system to operate within a safe region. The trained controllers will work as long as the state of the system remains within or close to that region of the state space. In our simulations there were no defined control actions for states outside the region. In practice a simple but safe control scheme could be used to return the system back to the operating region. For example, a simple rule based scheme could be hand crafted based on the common sense and incorporated in the knee and hip FLCs. Such a control system would have two sets of rules, one designed by the RL for the normal operating region and the other designed heuristically for the remainder of the state space that might be visited under abnormal conditions such as a fault or an unusually high disturbance.

It was shown that the RL was able to compensate for weak arm forces by identifying the system very quickly and raising the stimulation intensity just high enough to allow the maneuver to be successfully completed. In the experiment to minimize arm forces, the FLC-RL learned to increase the stimulus intensity to the hip and knee extensor muscles in order to reduce the arm forces, resulting in shorter and faster maneuvers (Figure 6.8). Since, the graphs are drawn after the seat-off moment, the arm force is high at the beginning of the maneuver. RL minimizes the integral of the arm force from the seat-off to the standing position. The minimization is achieved by reducing the average arm force during the standing-up and reducing the total time of the maneuver. The arm force increases again once the standing position is reached. This increase is because of the assumptions made in modeling the arm forces where we assumed that the vertical arm force should maintain a minimum upward velocity of 0.35 m/sec for the shoulder joint. This high arm force after achieving standing position is not realistic and is usually lower due to the loading of the legs by the FES. The model of the arm force can be improved by using a separate model to maintain standing position that will account for the lower arm forces and weight bearing by the legs. Because of such limitations in the model of the arm force, used in this study, more accurate models of the voluntary arm forces must be developed. The final control solution shown in Figure 6.8 is very similar to the open-loop maximal stimulation of the knee and hip extensor muscles. RL was able to reason these simple goal-seeking tasks out without any information about the system using only that obtained from its own exploratory interactions and a scalar reinforcement signal. Although these are simple examples they serve to illustrate the potential of the FLC-RL to deal with far less obvious situations.

In the experiment to minimize the knee terminal velocity, RL found that it could reduce the terminal knee velocity by not only modifying stimulation to the knee joint but also the stimulation to the hip joint, taking advantage of the dynamic coupling between the joints. Stimulation has shifted from the extensors to the flexors at just the right time to reduce the knee terminal velocity. This is a delicate task since the dynamics of the final stages of the standing-up motion is very sensitive to joint moments. Furthermore, because of the kinematic constraints, minimization of the knee terminal velocity also resulted in minimization of the hip terminal velocity. As indicated in Figure 6.9, the arm forces remained almost unchanged in a maneuver with minimal arm forces and minimal terminal velocities.

6.4.3 Heuristically chosen parameters and dimension of the state space

The choice of the learning parameters affects both the rate of convergence and the quality of the final solution. Some values could result in complete failure to learn. By trial and error, we found a set of learning parameters that resulted in convergence. However, we did not try to find the optimal parameters so further adjustment may provide faster convergence.

In practice we envisage that training sessions will be needed when fitting the neural prosthesis. It will be important to limit the number of learning trials required to converge to an initial useful control strategy. One possibility lies in the proper choice of the learning system structure including the learning rates of the RL algorithms, the number of the membership functions of the FLCs and the reinforcement signal. For example, at higher learning rates the learning process may become unstable. The higher the number of the membership functions the higher the number of the tuning parameters and therefore slower the learning. On the other hand, fewer membership functions could compromise the resolution and result in poor control. Therefore, the skill to properly choose the structure of the learning system is very important for speeding-up the learning and usually comes with practice.

As the dimension of the state space increases the number of learning trials required to form the value and action functions and the computational cost increase exponentially. In the experiment to reduce the terminal knee velocity it seemed reasonable to include joint velocities as inputs to the value and action functions. This modification increased the dimension of the state space from 2 to 4 which in turn increased the number of the tuning parameters by 266 times. As an example, if each dimension used 10 membership functions then the number of the network weights for 2, 4 and 6 dimensions would be 10^2, 10^4 and 10^6 respectively. Learning rate for the case with 4 inputs was very slow e.g. the velocity was reduced by 20% in 600 trials. Therefore, we did not include the knee and hip joint velocities as the input to the value and action functions. With the reduced set of the input variables that included only the angular positions of the knee and hip joints, it was shown that the RL could successfully learn the control strategies. One explanation is that the RL builds internal representations of the excluded or hidden state variables (Sutton and Barto, in press). On the other hand, one remedy to the "curse of dimensionality" in problems with many inputs is the use of multi-layered neural networks that are able to handle many input variables (Rummery and Niranjan, 1994). Another is to partition the state space into tilings each including only some of the dimensions as explained in (Sutton, 1996; Sutton and Barto, in press) rather than use our simple grid partitioning scheme. With FLCs however, it is straightforward to incorporate previous knowledge in the form of the rules and they have a better local representation than the neural networks.

6.4.4 Optimality of the controllers

In the simple double integrator, even the trajectories in the earlier stages of the learning process were close to the optimal solution although many more trials were needed for convergence to the optimal solution (Figure 6.6.a). In more complex situations the number of trials could be very high, however, in practice even sub-optimal controllers could give satisfactory performance. The RL uses a method similar to the gradient following procedure that could be trapped in local optima. Although this sub-optimal solution may be considered as practically sufficient, there are ways to improve the chance of finding the global optima in multi-modal search spaces. The RSU in Figure 6.3 is a mechanism that could avoid the local optima by selecting different exploratory actions. However, it is not a complete solution because the size of the exploratory actions must be limited to facilitate convergence and improve safety which, means it can help to escape only smaller hills in the multi-modal search space. Another more general approach is to repeat the learning experiment with different starting parameters.

6.4.5 Suggestions for further work and future practical implementation

The simulations demonstrated good recovery from transient disturbances such as those that may be expected due to spasticity or sudden actions of the upper body and good accommodation to slow changes in the system dynamics. These changes may be expected from FES induced muscle fatigue, slow changes in the subject's physical parameters such as weight loss/gain or slow changes in the voluntary control strategy due to the patient becoming more skilled in the maneuver.

The capability to adapt to the changes in the voluntary control strategy may be one of the strongest aspects of the RL opening up the possibility for mutual learning. This may provide a better "cybernetic interface" in which both the subject and the RL controllers learn to cooperate to perform the maneuver better since neither the FLC-RL algorithm or the human require explicit a priori models for learning. Interaction and reinforcement is all that is needed for the mutual learning to proceed.

In more conventional closed-loop FES controllers specialized sensors are chosen that monitor specific state variables and must be accurately aligned with the anatomy and precisely positioned in specific locations e.g. goniometers across lower limb joints. This may be inconvenient, particularly if the sensors are to be surgically implanted. RL however, has no such requirement and may use any available set of sensory signals that are sufficiently rich in information about the state of the system and the reinforcement signal. These could include sets of miniature artificial sensors located in convenient external places or implanted (Williamson and Andrews, 1997; Williamson and Andrews, 1996; Andrews and Williamson, 1997) or in combination with natural sources such as EMG or ENG using electrodes in the periphery or microelectrodes in the central nervous system. In such arrangements, the reinforcement signal, such as the knee velocity if the knee end velocity is to be minimized, may not be directly available. In such case it must be derived either intuitively using handcrafted rules or indirectly using supervised machine learning techniques as described in (Williamson and Andrews, 1996). The FLC-RL may provide similar flexibility in terms of the stimulation sites. For example, as an alternative to stimulating highly differentiated peripheral nerves it may be desirable to stimulate the spinal cord or the spinal roots and establish control despite the more complex responses. For example, stimulating the lumbar anterior sacral roots produces multiple muscle contractions that affect multiple joints in more than one degree of freedom (Donaldson et al., 1997; Rushton et al., 1997). The flexibility in the choice of inputs and the outputs comes from the fact that the RL process essentially learns associations between situations and actions. A further consequence of this feature may offer a measure of fault tolerance if there is a redundancy in the sensors and stimulus sites. Should a sensor or stimulus site suddenly or progressively fail to provide consistent signals or responses the FLC-RL may progressively learn to discount them from its control strategy.

To ensure patient safety during the initial training phase and subsequent use of the RL controller, we envisage an initial FLC-RL controller based on reliable handcrafted rules, for example, those commonly used in clinical practice (Wang et al., 1997; Wang and Andrews, 1994). This "training wheels" possibility is suggested by the results of the simulation to minimize both the arm forces and the terminal velocity of the knee joint. Our intuitive understanding of the system was used to hand craft the initial controllers so that it was possible to minimize both criteria. The results of investigating the effects of system changes suggest an alternative in which an initial controller could be pre-trained by applying the RL algorithm to a dynamical model approximately scaled to the individual patient. Of course, the latter would be feasible only if a model was available that also included the sensors. The latter may not be possible for natural sensors or when sensor alignment and position is uncertain. The subsequent learning process which, needs smaller number of trials to converge, could then continue to fine-tune the controller without compromising the patient safety.

6.5 Conclusions

The classic RL algorithms can be extended to the continuous state and action spaces using function approximation techniques. These algorithms were validated and performed well in continuous space, multi-controller problems and in the presence of the simulated complexities normally encountered in the FES control systems such as dynamic coupling. The RL was able to learn appropriate strategies to compensate for the weak arm forces and was able to simultaneously reduce arm force requirement and the terminal velocity of the knee joint. The FLC-RL was able to recover from simulated disturbances approximating those encountered in FES assisted standing-up in paraplegia. It may be possible to include a priori heuristic rule based knowledge in the learning system structure, which may accelerate the initial learning rate and provide safety. Although the method appears to be promising only the theoretical feasibility has been demonstrated, further work is required to demonstrate clinical feasibility.

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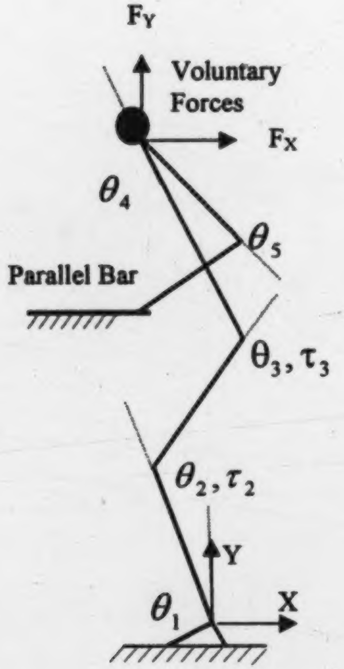
F_Y
Voluntary
Forces
F_X
θ_4
θ_5
Parallel Bar
θ_3, τ_3
θ_2, τ_2
Y
X
θ_1

Figure 6.1 Body segmental model of the arm-assisted standing-up. θ_i's are the angular positions of the segments measured from the previous segment (dashed lines). τ_i's are the net moments produced by the electrically stimulated muscles acting on the joints. The dynamics of the arms is divided into active and passive part as explained in the text.

(A) Control rules for F_X

V_X $X-X_C$	NL	NM	Z	PM	PL
NL	PL	PL	PM	PS	Z
NM	PL	PM	PS	Z	NS
Z	PM	PS	Z	NS	NM
PM	PS	Z	NS	NM	NL
PL	Z	NS	NM	NL	NL

(B) Control rules for F_Y

V_Y-V_{SET} Y	NL	NM	Z	PM	PL
VS	PL	PL	PM	PM	PM
S	PL	PM	PM	PM	PS
M	PM	PM	PM	PS	Z
L	PM	PM	PS	Z	Z
VL	PM	PS	Z	Z	Z

Figure 6.2 Rule base of the fuzzy logic controllers modeling the voluntary arm forces. The control rules for F_X (A) and F_Y (B) are given. X, Y, V_X and V_Y are the position and velocity components of the shoulder joint in the coordinate system shown in Figure 6.1. X_C = -0.1 m (center of the foot support area) and V_{SET} = 0.35 m/sec are used as setpoints for the horizontal position and the vertical velocity of the shoulder joint. The outputs of the controllers are the normalized F_X and F_Y that are then linearly scaled to their maximum values. The maximum values of F_X and F_Y are set at 150 N and total body weight respectively. **N** - Negative **P** - Positive **Z** - Zero **S** - Small **M** - Medium **L** - Large **V** - Very

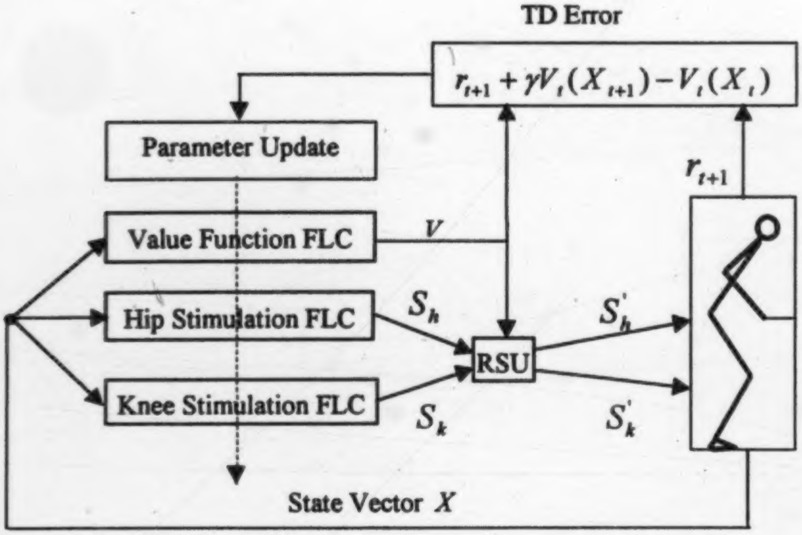
TD Error
$r_{t+1} + \gamma V_t(X_{t+1}) - V_t(X_t)$
Parameter Update
r_{t+1}
Value Function FLC
V
Hip Stimulation FLC
S_h
S_h'
RSU
Knee Stimulation FLC
S_k
S_k'
State Vector X

Figure 6.3 Structure of the reinforcement learning system. FLCs are used to represent the knee and hip joint stimulation pulsewidth controllers and the value function. Parameter update unit uses the TD error and the structural information of the FLCs to adjust their parameters. Random search unit (RSU) provides the exploration in the action selection. The detailed description of the learning system is given in the text.

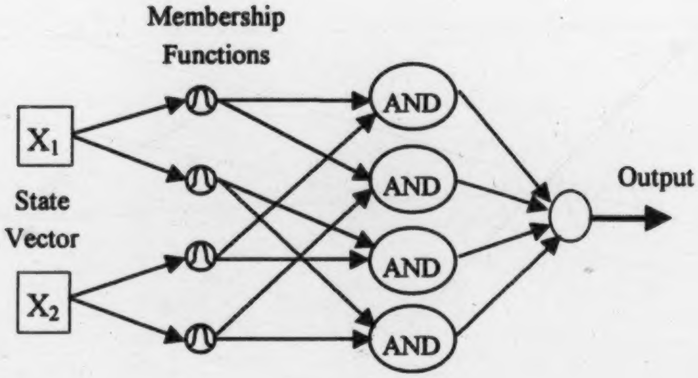
Membership
Functions
X1
State
Vector
X2
AND
AND
AND
AND
Output

Figure 6.4 Inference system of a FLC function approximator. For demonstration purpose, only two membership functions are used for each input variable. The actual number of the membership functions are shown in Figure 6.5.

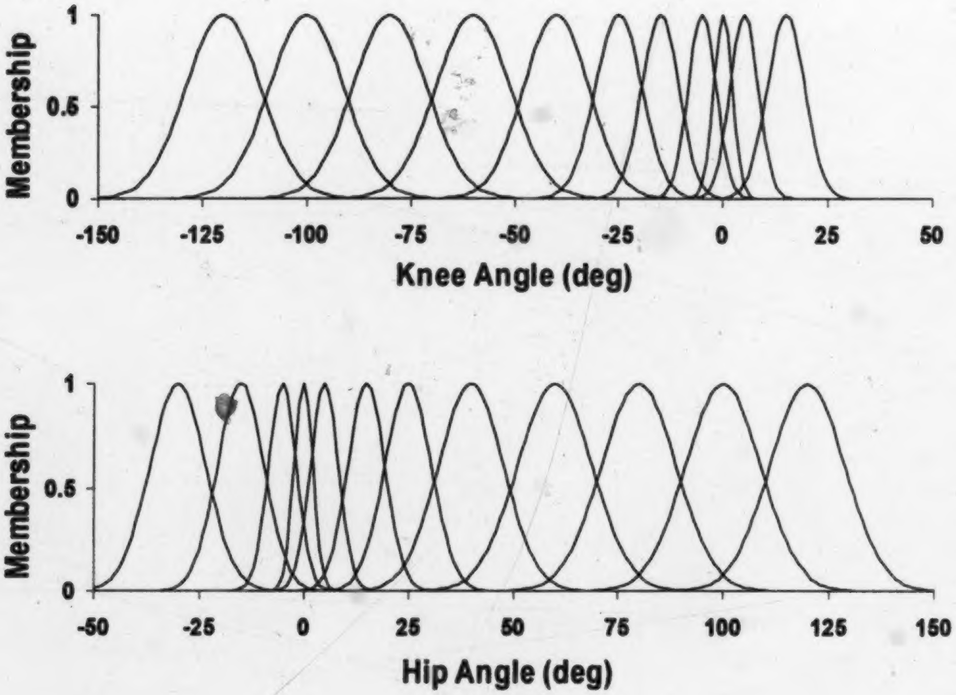

Figure 6.5 Gaussian membership functions used to encode the FLC inputs. Knee and hip joint angles are represented by 11 and 12 MFs respectively. The central values of the MFs are chosen with more concentration in the dynamically sensitive region around the standing position. The width of MFs are chosen for approximately 50% overlap between the neighboring MFs.

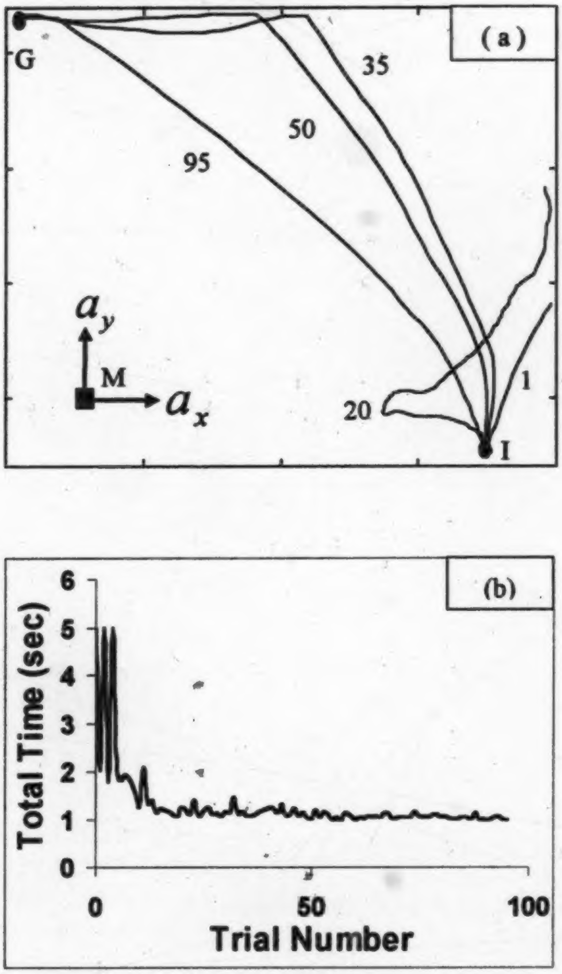

Figure 6.6 A unit mass in a 2D space controlled by reinforcement learning. In **(a)** a unit mass **M** is shown in a two-dimensional state space that is $2\,meter \times 2\,meter$ in size. Two FLCs control the accelerations a_x and a_y to move, in each trial, the unit mass from **I** (initial state) to **G** (goal state). The trajectories of **M** in different stages of learning, when the RL tries to find the quickest path from **I** to **G** are shown with the trial numbers next to them. The performance of the RL in reducing the time spent in each trial is shown in **(b)**.

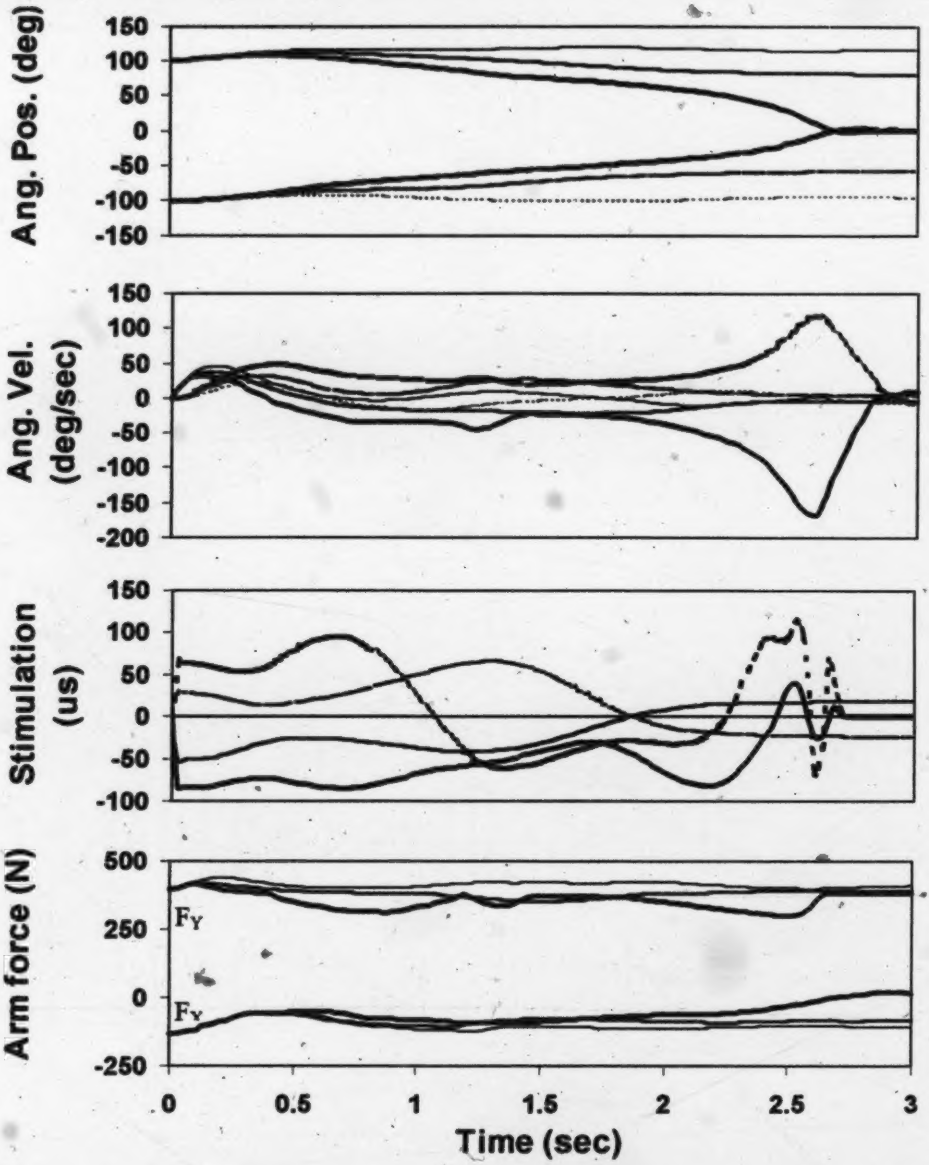

Figure 6.7 Performance of the RL when compensating for inadequate arm forces in standing-up. The results are shown for trial 0 (thin), trial 10 (medium) and after convergence in trial 29 (thick). Continuous and dashed lines represent the values corresponding to the hip and knee joints respectively. The stimulation to the knee and hip joint extensors are increased just enough to compensate for the weak arm forces. Note that the stimulation pulsewidth applied to the joints is always positive. The sign of the stimulation in the figures determines whether it is applied to the extensor or flexor muscles of the joint as explained in the text.

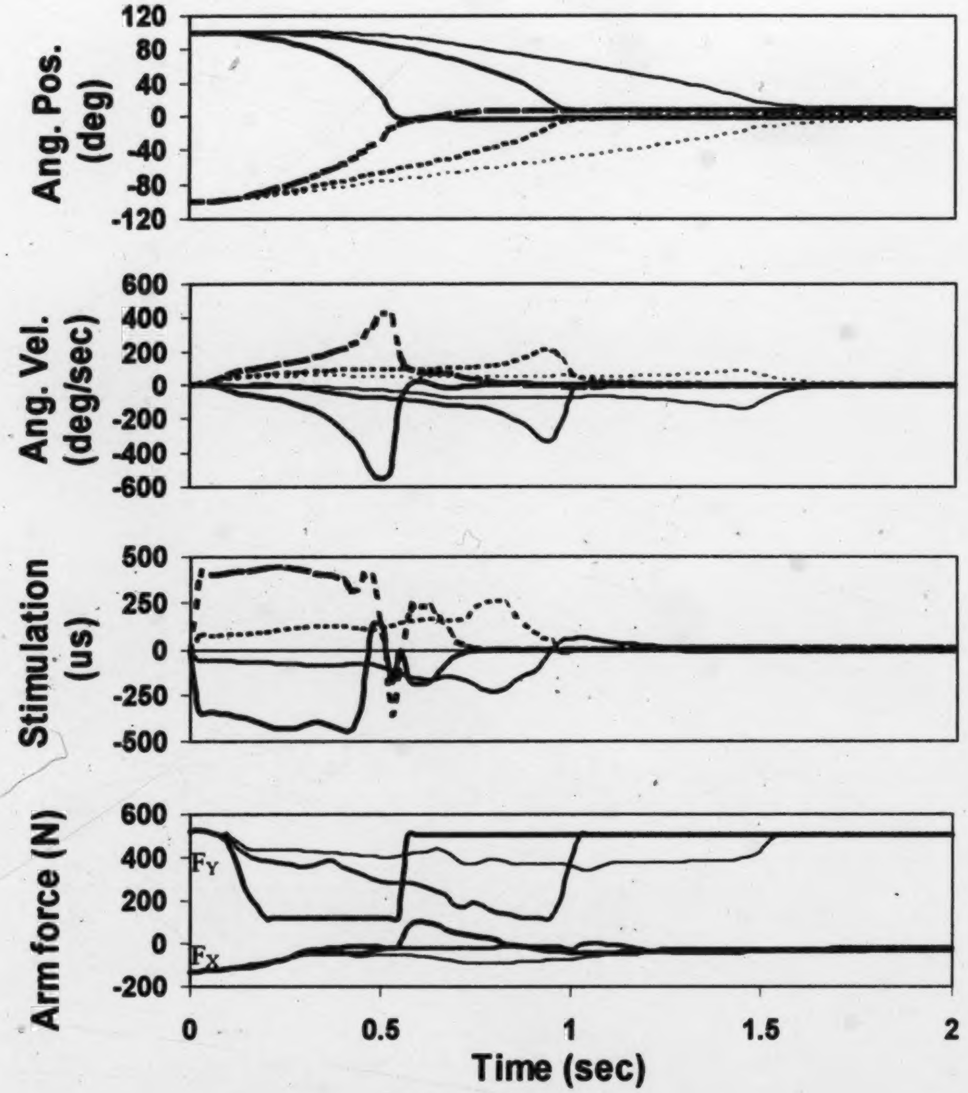

Figure 6.8 Performance of the RL when minimizing the arm forces. The results are shown for trial 0 (thin), 100 (medium) and after convergence in trial 276 (thick). Continuous and dashed lines represent the values corresponding to the hip and knee joints respectively. Since the graphs are drawn from the seat-off moment, the vertical arm force (**F_Y**) is high at the beginning. The value of **F_Y** during the standing-up maneuver is lower because the RL has raised the stimulation to the knee and hip joint extensors. However, **F_Y** increases after achieving the standing position, which is due to the modeling assumptions requiring the vertical arm force to maintain a minimum vertical velocity.

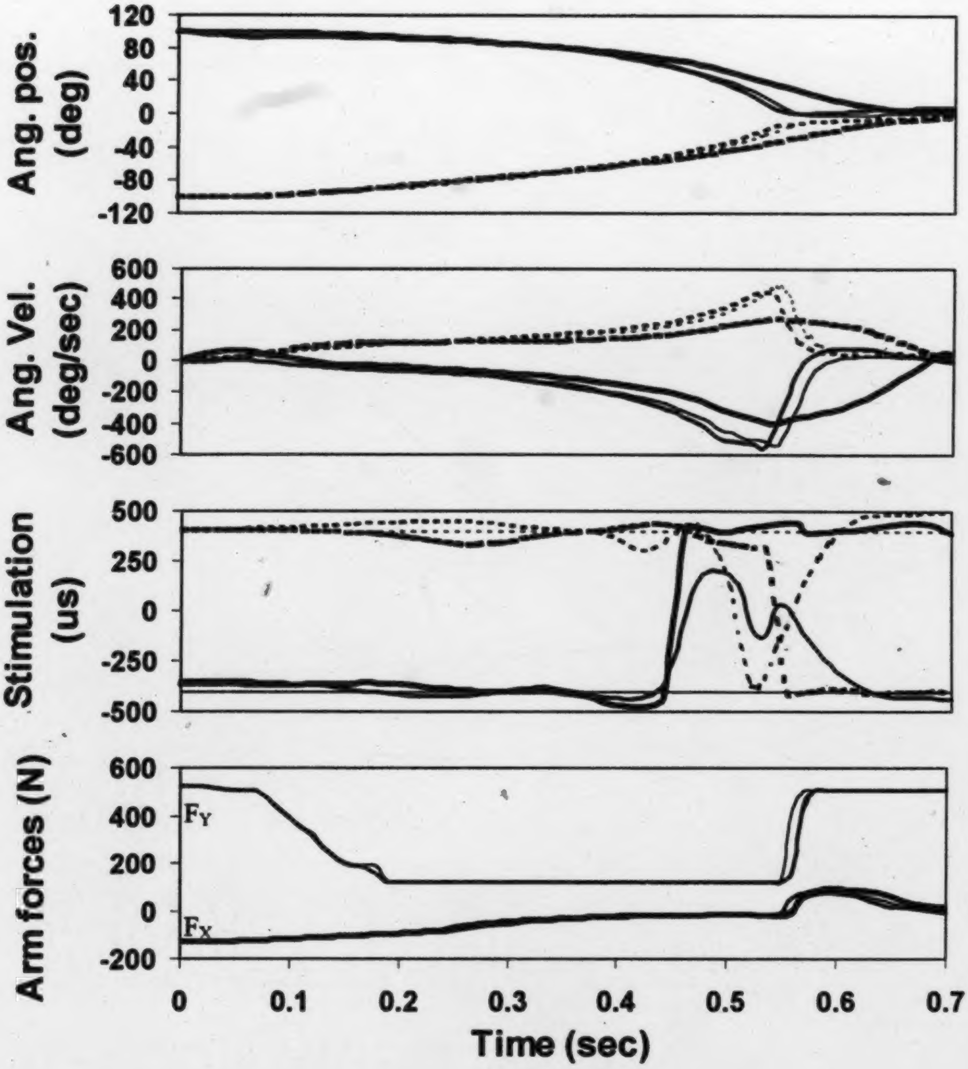

Figure 6.9 Performance of the RL when minimizing the KEV and arm forces. The results are shown for trial 0 (thin), 100 (medium) and after convergence in trial 238 (thick). Continuous and dashed lines represent the values corresponding to the hip and knee joints respectively. The RL has managed to intelligently modify the stimulation strategies to the knee and hip joints to reduce the knee end velocity from 490 °/sec in trial 0 to 440 °/sec in trial 100 and finally to 10 °/sec in trial 238. The knee end velocity is the velocity measured just before the passive joint structure starts to progressively reduce the knee velocity at knee angle = -10°.

Subject mass	59.0 kg
Subject height	1.78 m
Muscle fatigue time constant	105 sec
Muscle time constant	30 ms
Stimulation delay	50 ms
Initial Ankle angle	15°
Initial knee angle	-100°
Initial Hip angle	100°
Integration time step	0.005 sec
Maximum knee extensor torque	60.0 N.m
Maximum knee flexor torque	30.0 N.m
Maximum hip extensor torque	40.0 N.m
Maximum hip flexor torque	20.0 N.m
Shoulder offset angles	10 & 220°
Shoulder spring constant	10.0 N.m/rad
Shoulder damping constant	5.0 N.Sec
Elbow offset angles	-130 & -10°
Elbow spring constant	16.0 N.m/rad
Elbow damping constant	8.0 N.Sec

Table 6.1 Model parameters used in the RL simulations.

7 Optimal Trajectory Generation for Standing-up using Genetic Algorithms

7.1 Introduction

Standing-up is a biomechanically demanding maneuver that requires both sufficient joint moments and an appropriate multi-segmental coordination (Kelly et al., 1976; Riley et al., 1991; Riley et al., 1997). One possibility for a smooth transition from sitting to standing is for the leg joints to follow a set of predefined reference trajectories. For some researchers who were applying Functional Electrical Stimulation (FES) to restore standing-up in paraplegia, it seemed quit natural to use as reference, the joint trajectories recorded from healthy subjects (Quintern et al., 1989; Dolan et al., 1998). There are however, essential differences between the normal and FES assisted or other forms of impaired standing-up, which could make it impossible or inefficient to follow the normal trajectories.

The electrically stimulated muscles produce limited joint moments and fatigue faster than the naturally activated muscles. With such a limited joint torque, it may not be possible to follow the normal standing-up trajectories. There are also differences depending on the mode of standing-up (unassisted or arm assisted), initial conditions (leg placement, chair height and initial trunk angle), age related impairments, and anatomy of the subject that could influence the optimal and practical joint trajectories. Therefore, the joint trajectories for FES assisted standing-up or impaired elderly must be tailored to the needs and limitations of each individual to be efficient and practical.

Most of the studies relevant to standing-up, analyzed the existing situations in healthy or impaired individuals. The objectives were to characterize the movement patterns or quantify the biomechanical factors underlying the observed movement. Kelly et al. (Kelly et al., 1976) studied the sex and age related differences in standing-up patterns and concluded that there is none. Nuzik et al. (Nuzik et al., 1986) characterized visual patterns of sit-to-stand movement in normal subjects to be used by physical therapist as a standard to compare the movement patterns of patients and set treatment goals. Investigating the speed of rising, Pai and Rogers (Pai and Rogers, 1990) found that it affects mainly the vertical movement and not the horizontal movement. They suggested that the horizontal and vertical movements might be controlled independently. Riley et al. (Riley et al., 1991) examined the segmental contributions to the whole body motion and found that in a brief period following the lift-off, inter-segmental momentum transfer takes place. At this point, the forward trunk momentum is transferred to vertical momentum. Schultz et al. (Schultz et al., 1992) studied standing-up in a group of young and elderly and reported that all of them placed more importance on achieving better postural stability than diminishing the required joint moments. They also found that the postural stability was threatened most at lift-off from the chair and the maximum knee and hip joint moments that occurred at this time or shortly thereafter were well below the maximum voluntary joint moments. Doorenbosch et al. (Doorenbosch et al., 1994) compared the natural sit-to-stand transfer and a sit-to-stand transfer with full flexion of the trunk. The latter reduced the knee joint moment in the expense of increasing the hip and ankle joint moment. Hughes et al. (Hughes et al., 1996) investigated the functionally impaired elderly and reported that the knee extensor strength is a limiting factor in determining the minimum chair height from which they may rise. Riley et al. (Riley et al., 1997) compared the successful sit-to-stand in normal subjects to the failed sit-to-stand in balance-impaired elders. Failed trials were less energetic than the successful trials. They suggested that the weakness or coordination impairment or both might have been responsible for the failures.

All of the above studies analyzed existing sit-to-stand patterns in healthy or functionally impaired subjects but no attempt was made to explore possible patterns that might solve the impairment. The functionally impaired subjects may attempt some novel strategies to overcome their impairments that because of the motion complexity may constitute only a fraction of the possible strategies. Therefore, an extensive search is required to find, among many possibilities, those movement patterns that suit a functionally impaired individual. Pai and Patton (Pai and Patton, 1997) examined the set of center of mass (COM) velocity-position combinations for maintaining balance during seat take-off. Using a single-link inverted pendulum attached to the foot segment and an optimization algorithm, they showed that with a proper COM velocity during take-off, the balance can be maintained even if the center of mass is outside the base of support (BOS). The model was very simple and did not include multi-segmental interactions. With regard to the tracking controllers, the reference trajectories of the COM are not useful because, the muscle actuators primarily position the joints not the COM. Bahrami et al. (Bahrami et al., 1996) used a three-segmental model and an optimization method to generate the optimal joint trajectories that minimized the total joint torques and/or the total torque changes. The maneuver was assumed to start at seat-off and the trajectories were parameterized with piecewise linear curves. Minimization of total torque change resulted in smoother movement than minimizing total joint torques. Nevertheless, they concluded that the CNS uses a combination of these two criteria because it yielded trajectories closer to that measured in normal subjects. They did not minimize the maximum joint torques presumably because it could not be expressed mathematically in terms of the optimization parameters. Since, the motion started from seat-off, one important phase of standing-up which constitutes the trunk's forward momentum generation was ignored. It also seems improbable that criteria such as muscle force and total time of maneuver could be optimized. Because, these criteria can not be expressed, using continuous mathematical formulas, in terms of the optimization parameters.

The optimization methods in the above studies required differentiable mathematical formulations of the equations of motion and constraints in terms of the optimization parameters. This requirement is very restrictive for complex multi-segmental models and constraints that are difficult or impossible to formulate in terms of the optimization parameters (e.g. maximum joint torque or total time of maneuver). To overcome these limitations, we decided to use genetic algorithm (GA) optimization method which not only do not require differentiable or continuous functions but also can handle almost any kind of constraints. Clearly, there are many different cases of impairment to consider but, we will use a relatively difficult example to demonstrate a general approach for generating the optimal and safe joint trajectories. Here the GA will be used to generate the optimal joint trajectories for an eight-segment model of unassisted standing-up.

7.2 Methods

7.2.1 Model of Unassisted Standing-up

Unassisted paraplegic standing-up was modeled by eight segments including the foot, shank, thigh, trunk, upper arms and forearms. The segments were connected by nine frictionless pin joints to each other and to the ground (Figure 7.1). Ankle, knee and hip joints were actuated by torque producing muscles while shoulder and elbow joints were moving freely. The directions of the forces developed in the pin joints located under the heel and metatarsal head were used to detect feasible movements in sagittal plane. This method takes into account both the position and velocity of the center of mass (COM) and is different from the traditional notion of balance that relates the feasible movements to the position of the COM only (Patla et al., 1992). The subject was assumed to have balance as long as the vertical forces at these joints were in positive Y direction. The mass center of each segment lied on the line connecting the two adjacent joints and did not change during the motion. Typical male proportions were used to determine anatomical parameters (Winter, 1990). SD/FAST (Symbolic Dynamics Inc., USA) was used to formulate the equations of motion, which were then integrated using a variable step 4th order Runge-Kutta method.

7.2.2 Genetic Algorithms Optimization Method

Genetic algorithms are optimization procedures that are based on the mechanics of natural selection and genetics to produce increasingly fitter populations (Goldberg, 1989). They start with a population of randomly chosen chromosomes and evolve toward higher fitness by applying genetic operators such as reproduction, crossover and mutation.

A chromosome, is a candidate solution, for example, it can be a binary coded string of all the design variables (Figure 7.2). Reproduction produces a new generation where chromosomes with higher fitness have better chance for further reproduction. Crossover results in randomized, yet structured information exchange between chromosomes to produce new patterns while mutation maintains diversity (Figure 7.2.B and C). This reproductive cycle is called evolution and continues until optimization of an objective function is reached.

In contrast to other optimization methods, GA only uses the value of the objective function and therefore, the function does not need to be continuous and differentiable. GA can work with various types of variables at the same time as long as they can be encoded in a binary string. Instead of a single point, GA simultaneously operates on a group of points within the search space. This increases efficiency in searching large spaces and robustness in finding global optimum of multi-modal functions (Goldberg, 1989).

7.2.3 Formulation of the Optimization Problem

To find optimal joint trajectories, they were first parameterized and then the parameters were optimized by applying the GA. Total time of the sit-to-stand maneuver and therefore the total time of the joint trajectories was fixed at 2.5 sec. Motion was assumed to start with the trunk moving forward while the subject is on the chair. Other joints could start moving anytime as the subject lifts-off the chair. Five 5th order trajectories with zero initial and final velocities and accelerations were used. One trajectory for the knee allows only extension with initiation time as the parameter. Two trajectories for the hip allow forward trunk motion (hip flexion) followed by hip extension. The fractions of time for each trajectory and joint position in via point (the transition point from the first to the second trajectory) were the parameters. Two trajectories for the ankle joint allow forward shank motion followed by the return to the vertical position. The parameters were the initiation time, the fraction of time for each trajectory and the ankle position in via point.

The Six tuning parameters of the five trajectories were coded into a GA chromosome using eight-bit binary numbers for each variable, resulting in chromosomes of length 48. The GA randomly selects the parameter values for all the chromosomes in the first generation, applies them to the model subject and measures their fitness. The objective is to increase this fitness measure from generation to generation until the convergence to the optimal solution is reached. Population size of the GA was 100. Tournament selection method was used for reproduction and the probability of crossover and mutation were 0.8 and 0.05 respectively.

At each stage in the process of evolution, the GA attempts to maximize the fitness function for each candidate solution. This is equivalent to minimization of the objective function because, the fitness function is usually obtained by subtracting the objective function from a constant value that is higher than all the possible values of the objective function. The objective function was a weighted sum of five criteria as follows:

$$Objective\,Funcion = w_1.LOB + w_2.\tau_{total} + w_3.\tau_{\max,a} + w_4.\tau_{\max,k} + w_5.\tau_{\max,h}$$

Where,

$w_1, w_2, \ldots w_5$ are the weightings of each criteria in the objective function.

LOB is a measure representing the number of time steps during a maneuver in which, the model is out of balance. Minimization of LOB prevents the loss of balance. The lack of balance is detected by the direction of the foot reaction forces.

$\tau_{\max,a}$ is the maximum ankle joint torque during standing-up.

$\tau_{\max,k}$ is the maximum knee joint torque during standing-up.

$\tau_{\max,h}$ is the maximum hip joint torque during standing-up.

τ_{total} is the total joint torque defined as:

$$\tau_{total} = \sum_{sit}^{stand} (\tau_a^2 + \tau_k^2 + \tau_h^2)$$

Where, τ_a, τ_k *and* τ_h represent the ankle, knee and hip joint torques respectively.

Equations of motion and the GA algorithms were programmed in C and implemented in Labwindows/CVI (National Instrument, USA) environment. An animation capability was also programmed to visualize the developed motion strategies during and after the optimization.

7.3 Results

In all of the optimization experiments, since the first generation candidate solutions (joint trajectories) were chosen randomly, they were representative of movement patterns that were both out of balance and required very high joint torques. The GA however, in the process of evolution extracts and combines the useful sub-patterns of these initial trials to form better solutions and finally forms optimal patterns based on the given criteria.

Four optimization experiments were performed as follows:

OPT1: Only the LOB was minimized, i.e., $w_1 = 1, w_2 = w_3 = w_4 = w_5 = 0$.

OPT2: Maximum torques were minimized, i.e., $w_3 = w_4 = w_5 = 1, w_1 = w_2 = 0$.

OPT3: Total joint torques were minimized, i.e., $w_2 = 1, w_1 = w_3 = w_4 = w_5 = 0$.

OPT4: All the criteria were minimized, i.e., $w_1 = w_2 = w_3 = w_4 = w_5 = 1$.

Figure 7.3 shows the performance of the GA in OPT1, where, the GA improves the best solution in the population from generation to generation. Even the best solution in the first generation was 38 time steps out of balance. It took 8 generations or 800 sit-to-stand trials to minimize the out of balance instances to zero. Stick figures of the optimized movement pattern and the trajectory of the COM for OPT1 are presented in Figure 7.4.

Trajectories of the joints and the COM and the joint torques for the optimal solutions in different optimization experiments are compared in Figure 7.5-8. The important parameters of the four optimization experiments are compared in Table 7.1.

7.4 Discussion

The GA was able to robustly perform global optimization of the joint trajectories and converge to the optimal solution in all cases. Unlike, the majority of the optimization methods, the GA did not require the mathematical formulations of the equations of motion or the constraints in terms of the optimization parameters. This requirement limits the optimization to very simple models and excludes some forms of optimization criteria (Pai and Patton, 1997; Bahrami et al., 1996). For example, maximum joint torques can not be expressed in terms of the optimization parameters beforehand. The GA developed here works with a simulated subject and there is no limitation on the complexities that might be included in the simulation model. For example, discontinuous and non-differentiable elements can be included in the simulation. The complexity can slow the GA but can not fail it. Therefore, the GA broadens the range and complexity of the optimization problems that can be solved.

As the result of these capabilities, we were able to include the arms in the model and handle criteria such as minimization of the maximum joint torque and loss of balance instances. In the model, the arms were hanging from the shoulders without any actuation. The GA in OPT1 tuned the trajectories of the ankle, knee and hip so that the arms remained very close to the trunk. This was necessary to minimize the number of dynamically unbalanced instances. This is an evidence that the GA could handle complex systems.

The simulation model used in this study was a simplified model of the reality, which might affect the results. For example, standing-up was limited to sagittal plane and segments were modeled with rigid bodies. Unlike many studies of standing-up that assume the arms are crossed over the chest, in our model, they were left hanging from the shoulder joint and could move freely. This was done to test the GA with more complexity but the results are expected to differ from those in the literature.

The optimal movement pattern in OPT1 uses an extensive trunk flexion and velocity to move the COM over the base of support and build enough momentum before lift-off. The motion of the trunk is also synchronized with the initiation of ankle and knee joint motion so that the subject is in the state of dynamic balance at lift-off. The extensive trunk movement needed higher hip joint torque and resulted in higher velocity, and range of motion in the hip joint. This extensive trunk movement however has considerably reduced the knee and ankle joint torques. Similar patterns are present in other optimization experiments where, the extensive trunk momentum is used to reduce the knee and ankle joint torques. Apparently, the momentum buildup in the trunk is not wasted but is transferred to the other segments as suggested by Riley (Riley et al., 1991).

This result has practical importance because it suggests that an altered movement pattern can make use of the higher strength in one or more muscles to compensate for the impairments in the others. We suggest the following procedure for the rehabilitative use of the technique. First, the physical properties and impairments of the subject should be included in the simulation model and optimization criteria. Second, the GA optimization should be performed to find an optimal movement pattern to prevent for example the loss of balance. Once the optimal movement patterns are known, they can be used, at least, in two ways. One is the rehabilitation of the weak points such as strengthening those muscles that could make the suggested movement pattern possible (Hughes et al., 1996). Another use of the optimal movement patterns may be in training the functionally impaired individuals. For example, sensory measurements of the joint trajectories during the actual sit-to-stand trials can be compared to the optimal trajectories. Then audio or visual biofeedback signal can be used to signal the subject on what he/she is doing wrong and how it can be corrected. In the case of standing where the target trajectories are easily known (maintaining upright position), Wu used a similar technique for postural training of elderly patients during standing (Wu, 1997). Therefore, it might be possible to extend this training procedure to sit-to-stand maneuver.

OPT2 minimized the maximum joint torques in ankle, knee and hip joints simultaneously. Although each joint's torques in some instances is higher than that obtained in other optimization experiments, the sum of the maximum torques is the lowest in Table 7.1. The weightings of the criteria in the objective function can be changed to accommodate the situations where the maximum torque in one joint needs to be minimized. For example, if the minimization of the knee joint torque is of higher importance, its weighting (w_4) in the objective function can be increased relative to the others. As shown in Table 7.1, although OPT2 minimized the maximum torques and not the LOB, the time steps in which LOB occurs is only 18 out of 250 (2.5 sec total time). It is not clear how many LOB time steps can cause total failure of standing-up. A small number of LOB may be tolerated without failure if they are not succeeding each other. This however needs further study to clarify the conditions and the pattern of LOB in which the motion can be completed without falling. The motion patterns and joint torques in OPT2 is closer to OPT1 than the others. This might suggest that there is compatibility between the minimization of the maximum joint torques and preventing the LOB. Therefore, both can be achieved simultaneously with little compromise. For example, a small change in maximum joint torques may eliminate the 18 LOB in OPT2 and result in a balanced sit-to-stand with minimized joint torques. This should be explored in further optimization experiments.

OPT3 achieved the lower total joint torque (loosely related to the muscle energy expenditure) by primarily postponing the lift-off time. By doing this, it minimized the total activation time of the ankle and knee joints. LOB in this case was 48 which means it may end up in failure. Therefore, the total joint torques must be optimized while minimizing the LOB so that the resulting motion is a dynamically balanced motion.

OPT4 combined all the criteria. Since it had to compromise among the possibly conflicting criteria, it was not able to achieve a balanced movement pattern while minimizing the other criteria. Therefore, it might be suggested that some of the criteria introduced in the objective function are conflicting each other and some should be compromised to achieve the minimization of the others. It is not known whether the CNS optimizes the natural sit-to-stand motion or what criteria are optimized. Schultz (Schultz et al., 1992) showed that at lift-off, both young and elderly placed more importance on achieving acceptable postural stability than reducing the required joint moment. It seems that in healthy subjects who can produce a good deal of joint torques (Schultz et al., 1992), the reduction of joint torques is not as important as maintaining balance specially if it requires a an unusual movement pattern such as extensive trunk movement. So, is the CNS minimizing it's own activity by simplifying the control? Does the CNS continually improve a control or tries to maintain a non-optimal but working controller? We can not quantify the neural activity of the CNS and therefore, we can't examine whether it is optimized or not. The answer to these questions has to await further studies although, it may not really matter to a healthy subject. For a functionally impaired person however, it is important to optimize the use of the limited resources. Bahrami (Bahrami et al., 1996) suggested that a combination of total joint torques and total joint torque change might be optimized by the CNS. However, they only investigated these two criteria. Therefore, it is premature to suggest whether the CNS performs optimization or what is optimized in natural sit-to-stand.

By comparing the different optimization experiments in this study, it seems that OPT1 is the most practical one. The limitations of the impaired subject can be included in the simulation model such as the limited joint torque. Then OPT1 can be used to find a movement pattern that is always in dynamic balance. Fortunately, a dynamically balanced motion requires moderate joint torques, which is apparent from the similarities between the results of the OPT1 and OPT2.

Finally, the technique introduced here may be helpful in implementing the trajectory tracking FES controllers. Trajectory tracking controllers need appropriate trajectories and a way to realize them. Here we only suggested a way to find the optimal trajectories. These trajectories might be implemented using the error driven controllers such as the PID or even a more sophisticated controller design method similar to that described in chapter five. The latter used the GA optimization method to find the appropriate muscle stimulation patterns to follow the given trajectories.

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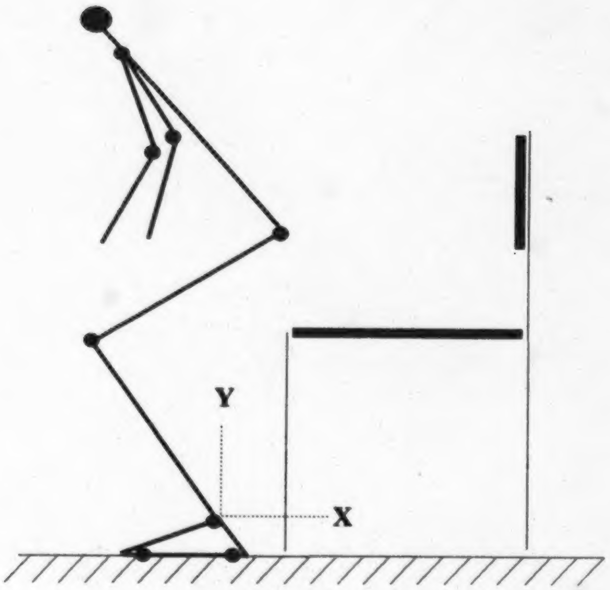
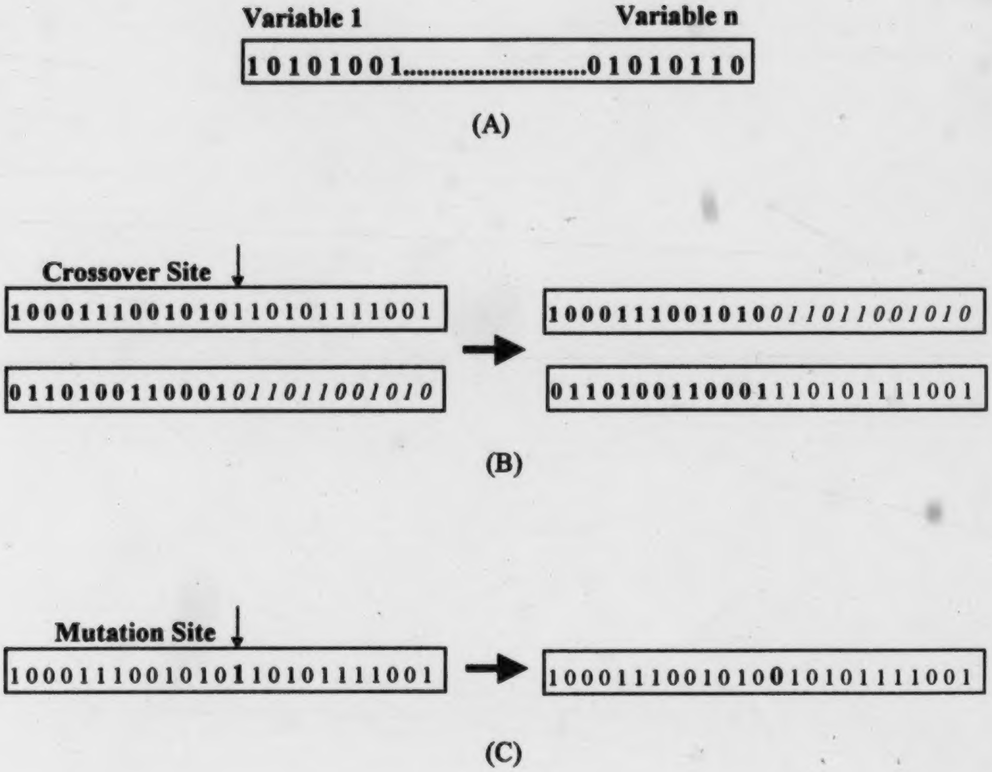


Figure 7.1 Body segmental model of standing-up. Ankle, knee and hip joints are actuated by torques generated by the leg muscles. The joints connecting the foot to the ground are used for balance detection and the remaining joints are moving freely. Subject mass = 70 kg, Subject height = 1.75 m



Variable 1
Variable n
10101001..........................01010110
(A)
Crossover Site
1000111001010110101111001
0110100110001011011001010
1000111001010011011001010
0110100110001110101111001
(B)
Mutation Site
1000111001010110101111001
1000111001010010101111001
(C)

Figure 7.2 Structure of the Genetic Algorithm optimization method. In (A) a chromosome is shown containing all the tuning variables coded into binary numbers. The crossover and mutation operations are demonstrated in (B) and (C). The chromosomes before and after operation are shown in the left and right respectively.

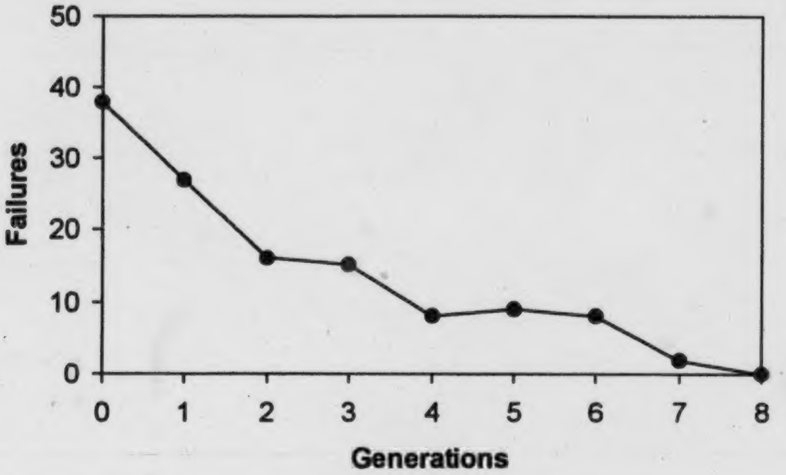


Figure 7.3 Trend of the objective function in OPT1 vs. generations. The objective function in OPT1 is the number of time steps during standing-up in which the model subject loses its balance or fails.

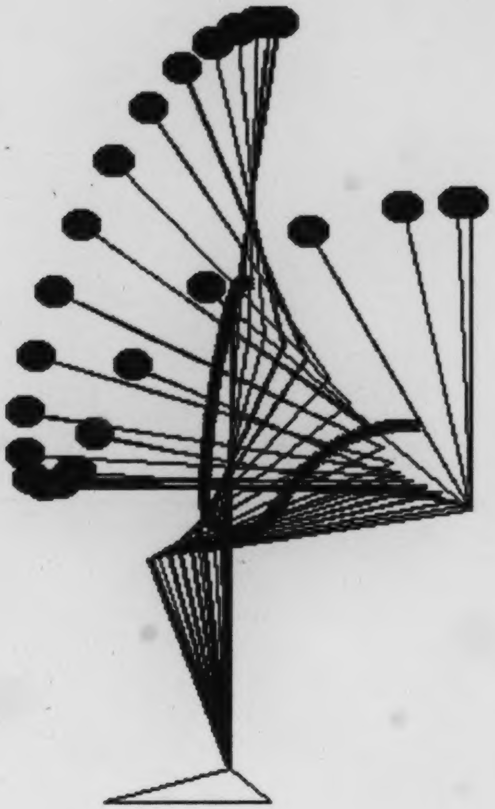


Figure 7.4 Stick figures (intervals of 100 ms) representing the optimal movement pattern in OPT1. In OPT1, the loss of balance is minimized. The trajectory of the COM is also shown. The arms are not drawn for clarity.

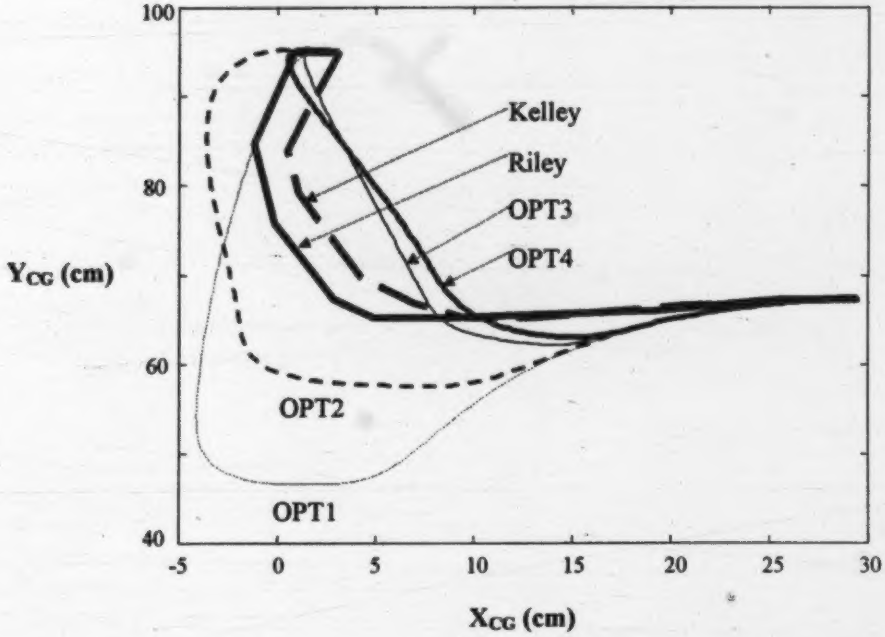


Figure 7.5 Trajectories of the COM in normal and GA-optimized standing-up maneuvers. 'Kelly' and 'Riley' are trajectories of the COM in normal subjects adopted from (Kelly et al., 1976) and (Riley et al., 1991) respectively. The position of the COM is measured in the coordinate system shown in Figure 7.1.

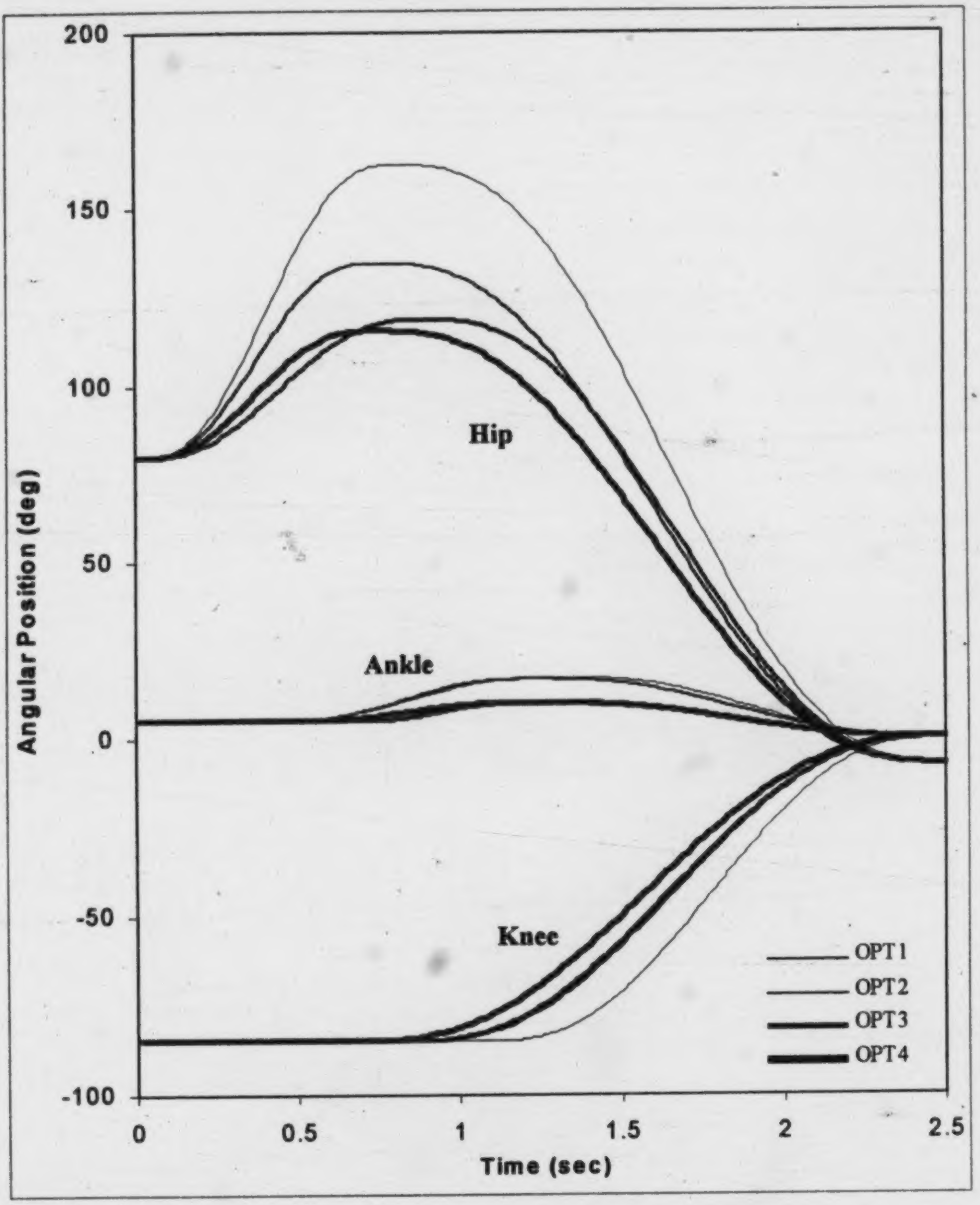


Figure 7.6 Angular position trajectories for GA-optimized standing-up maneuvers.

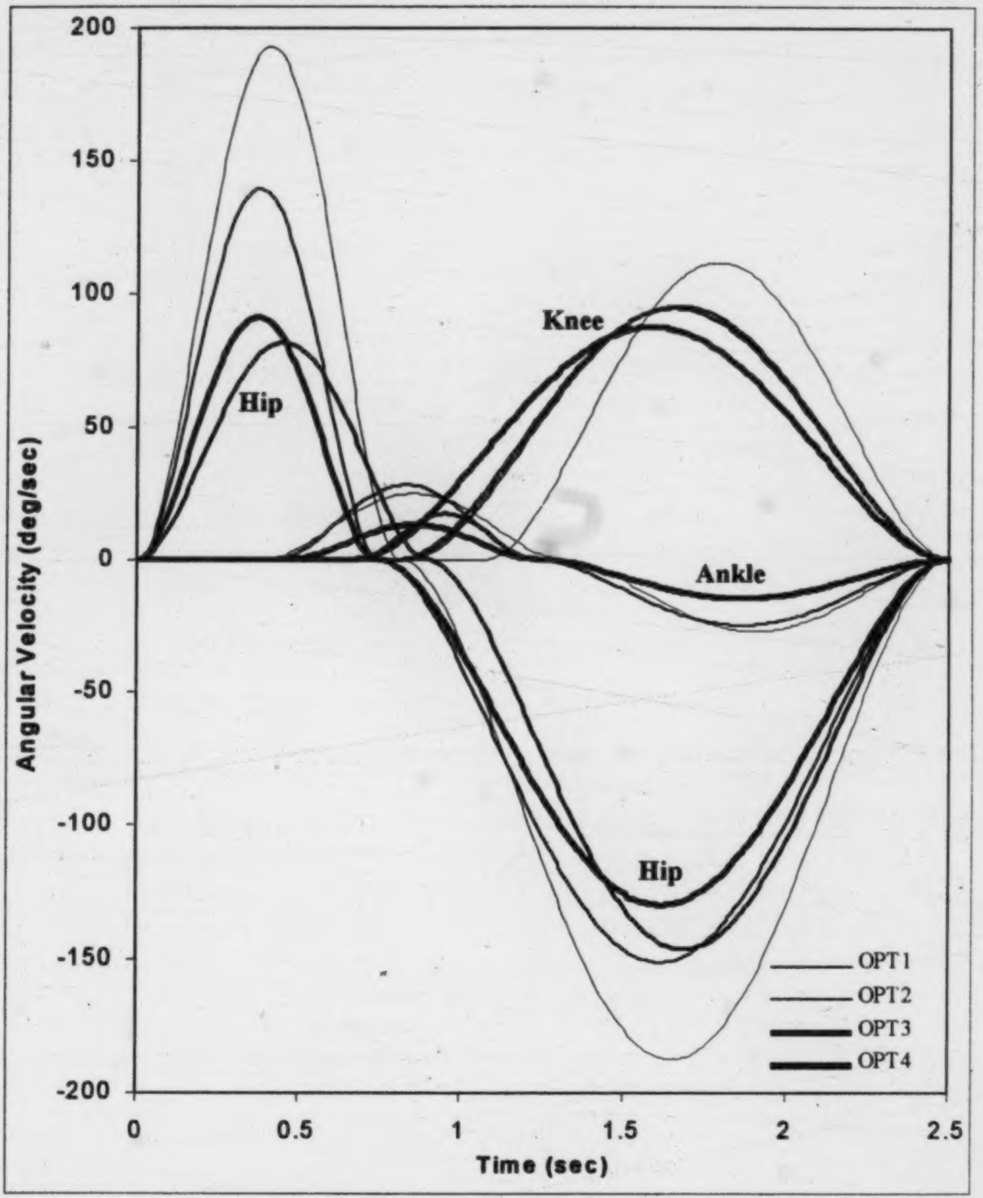


Figure 7.7 Angular velocity trajectories for GA-optimized standing-up maneuvers.

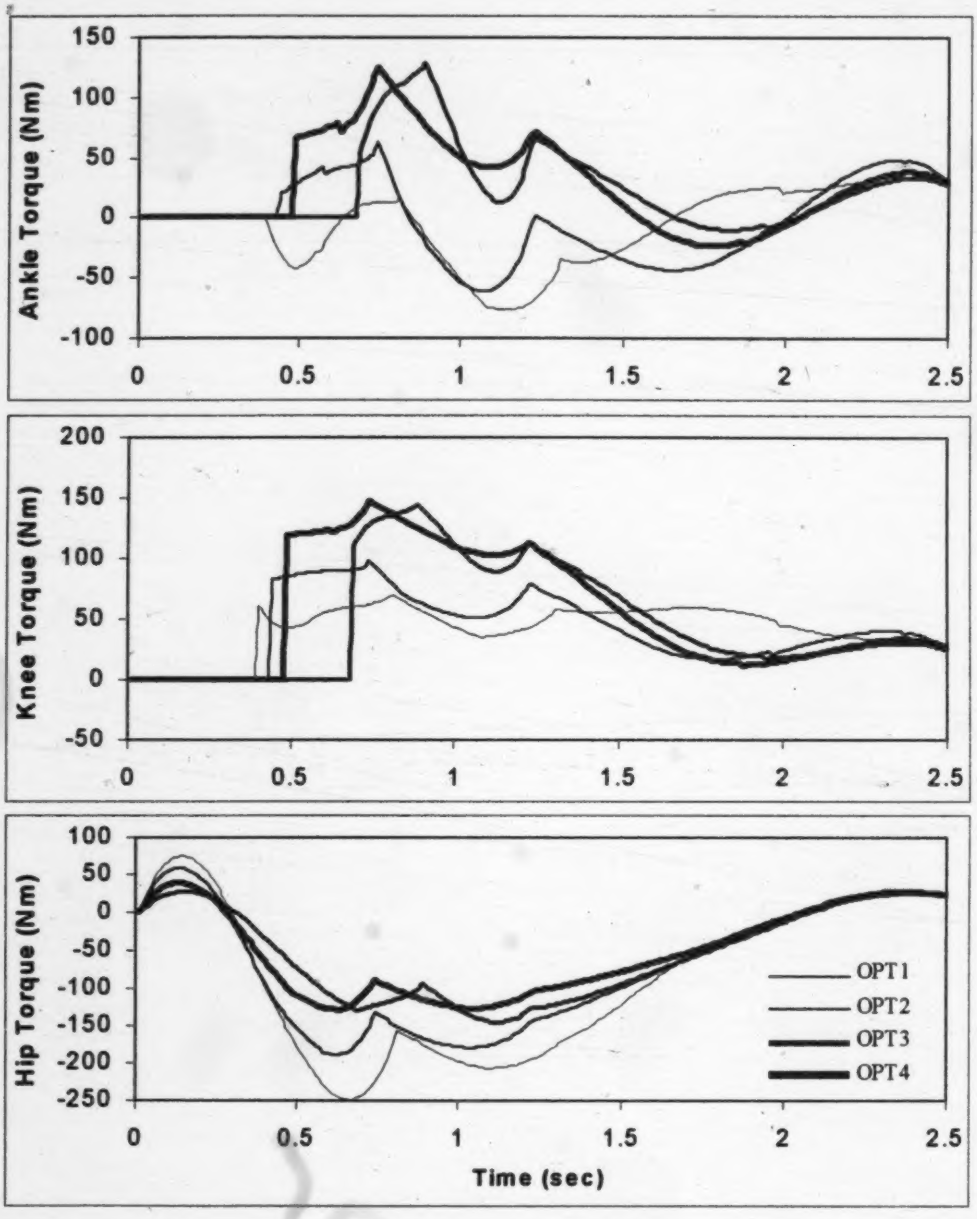


Figure 7.8 Joint torques for GA-optimized standing-up maneuvers. The torques at the ankle and knee joints are zero before the lift-off from the chair.

	Lift-off Time (sec)	X_{CG} at lift-off (cm)	$\tau_{\max,a}$	$\tau_{\max,k}$	$\tau_{\max,h}$	# of LOB (out of 250)
OPT1	0.4	15.6	-76.4	68.1	-249	0
OPT2	0.44	16.5	63.6	98.4	-189	18
OPT3	0.69	16.1	129.6	145	-146	46
OPT4	0.49	19.2	124.8	146	-127	69

Table 7.1 Important parameters of the GA-explored movement patterns. The results of four movement patterns, optimized for different criteria, are given.

8 Discussion

Control methods in FES assisted mobility restoration in general, and FES assisted standing-up in particular, are still primitive and clinical applications require the development of efficient, safe, and reliable controllers. The commonly used open-loop control methods for standing-up are incapable of handling the complexities such as nonlinearities, time variations and man-machine interactions. These are serious and challenging problems and the conventional control theory has no concrete solution to offer.

The main objective of this thesis was to develop a methodology for designing stimulation controllers for FES assisted standing-up in paraplegia. In FES assisted standing-up, the paralyzed leg muscles are activated by electrical stimulation and the arms are controlled by the CNS. Such a configuration is unique from the point of view of the control designer. Because, the controller must not only deal with the nonlinearities, couplings and time-variations in muscle actuators and skeletal system but also it must synchronize itself with the voluntary control of the subject. All these must be done while improving performance, evaluated with the required arm forces, smooth trajectories, muscle energy expenditure, and safety. Because of the great variations among paraplegics and time-variations in each individual, we were interested in a methodology that could tailor the controller to the needs of each individual and adapt to the time variations.

When the controlled system is too complex, one easy solution is to use simple ad-hoc controllers in the expense of performance. Several experimental controllers were suggested such as open-loop on/off control (Bajd et al., 1981; Petrofsky et al., 1984), open-loop control based on the muscle activation patterns in healthy subjects (Kagaya et al., 1995), Closed-loop on/off control (Mulder et al., 1992; Dolan et al., 1998), and PID control (Ewins et al., 1988). None of these methods offered a systematic approach to handle the main problems of the FES assisted standing-up and therefore, performance suffered.

An alternative approach offered by the control theorists is the development of controllers using accurate mathematical models of the system. However, accurate model of the FES assisted standing-up is too difficult to develop. Even, simpler models of musculoskeletal systems are out of reach for the current control methods not mentioning the man-machine interactions. Another difficulty with the model-based control methods is that the detailed parameters of the models are difficult to obtain for a living person. Therefore, model-based methods have been investigated in simpler situations such as the control of single muscle force or single joint position (Bernotas et al., 1987; Wilhere et al., 1985; Hatwell et al., 1991).

The control design approach adopted in this thesis is based on learning with interaction. At the beginning, the controller has no knowledge of the system or may be initialized with simple rules to enable a safe but crude control of the system. The learning algorithm then interacts with the system by repeatedly applying the initial controller. In the process of repeated trials, the learning algorithm learns from successes and failures and improves the initial controller based on the given objectives. The objectives might include different kinds of performance indices relevant to the quality of FES assisted standing-up. Two machine learning techniques, GA and RL, were used for this purpose. These learning algorithms stored the learned information in either ANN or FLC, which were the actual stimulation controllers.

Around the main theme of the thesis just explained, more studies were performed that not only led us to the adoption of the main theme but also helped us to implement it. First was the development of a model of standing-up. Although, the control methods in this thesis are model-free, we needed a simulation model to evaluate the controllers. This was necessary for safety reasons and development of a controlled environment for evaluation and comparison of the controllers. We developed a model of FES assisted standing-up with the main features being the inclusion of the closed-chain kinematics and a model of the voluntary arm forces. This model was then used to evaluate and compare all of the control methods in the thesis. First, simple open-loop and fixed-parameter closed-loop controllers, used in the past by other researchers, were compared. This comparison revealed the main control problems of FES assisted standing-up and led us to the adoption of machine learning techniques. The model of standing-up was then used to evaluate two machine learning techniques, GA and RL.

The whole thesis deals with the arm-assisted standing-up except for the final chapter where, the GA is used to generate the optimal trajectories for unassisted standing-up. The objective was to optimize the joint trajectories for the limits and constraints of an individual paraplegic. Here, we did not deal with the control problem, i.e., we assumed that a controller might be found to execute the given trajectories and we only explored the generation of optimal trajectories for such a controller. The technique was applied to an eight-segment model of unassisted standing-up, which is a relatively complex optimization problem. The results of this study turned out to have potential application in other situations such as training of the functionally impaired elderly.

The following sections include the discussion of the results in each chapter.

8.1 Model of the Voluntary Arm Forces

Neural network models successfully cloned the voluntary control of the arm forces during FES assisted standing-up. The models were accurate and performed well on both the training and validation data. Good performance on the validation data, which was from standing-up trials never used in the model training, showed that the models were able to generalize to unseen situations.

The mere fact that a model of the voluntary arm forces could be developed showed that the subjects developed personal control strategies and consistently executed them from trial to trial. There were striking similarities among the subjects in the way they controlled the arm forces but there were also differences attributed to the subject-specific parameters such as the level of injury and experience in the use of FES. We suggest that the unique role of the arms in arm-assisted standing-up, which is to provide balance and help in rising, might be responsible for the consistency and similarities. The specific requirements of the arm assisted standing-up, forces the CNS to develop focused strategies to control the arms. This in turn, reduces the variability and makes it easier to develop the ANN models, a condition that may not exist in other voluntarily control activities.

The consistency of the control strategies and similarity among the subjects also verified our assumptions in developing the qualitative FLC models of the arm forces in chapter 3. Our fundamental assumption was that there is a consistent pattern underlying the control of arms in standing-up, i.e., there are control rules that more or less govern the decision making process for the arms. These rules were then implemented using the FLC.

The ANN models that clone the voluntary control strategies of the individual paraplegics may be used in different ways. They can be used in conjunction with the lower extremity models to develop more realistic models of the paraplegics. These realistic models then can be used as the virtual subjects to test the controllers. For example, they can be used by the GA and RL to perform the initial stage of learning. The controllers designed in this way will be tailored to the needs of the virtual subject. The final fine-tuning of the controller could be performed on the real subjects. The models of the voluntary control strategy can also be used in any application that requires the predictions of the voluntary arm forces. The ability to predict the arm forces could be used to plan ahead and design more efficient FES controllers.

8.2 Model of Standing-up

The computer model of the arm assisted standing-up in paraplegia was developed primarily as a virtual subject to evaluate the new control strategies proposed in this thesis. This was necessary because the proposed methods were new and needed evaluation before experimental application. There was also a need for evaluation and comparison of different controllers in a controlled environment as the inter-trial and inter-subject variability excludes the use of the real experiments for this purpose.

Since, the controllers proposed in the thesis were model-free techniques, no knowledge of the computer model was used in designing them. Ideally, these controllers will be implemented on the real subjects without a need for the computer models. In model-based methods, the accuracy of the model is of utmost importance because, the controller parameters are obtained using the model parameters. The computer model here was only used to demonstrate the efficiency of the proposed control methods and therefore it was developed to include those features that make control difficult. This provided us with a tool to test the proposed controllers, at least in a simulated environment. We also tried to keep the model as simple as possible because in this way, it was computationally manageable and it was easier to interpret the results. As the result of the simplifications, the model predictions may be inaccurate. This is not however, very important because the controllers will not be designed using this models. We think that a controller's capability in learning to control such a model without knowing anything about it, is a demonstration that it has the capability to control the real entity represented by the model.

Despite the simplifications, the model had two new features that were also the main contributions to the modeling of standing-up. These were the closed-chain configuration, which is formed in the arm assisted standing-up, and the model of the voluntary arm forces. Because of their complexity, previous models of standing-up in the literature have ignored these two features. We included these features because they are important in demonstrating the capabilities of the controller. Closed-chain formation is a highly coupled and kinematically redundant which makes it difficult to control. The voluntary arm forces represent the man-machine interactions that require a FES controller capable of mutual learning. The FES controller should be able to coordinate itself with the voluntary control in pursuit of the common objectives.

The verification of the multi-segmental models of musculoskeletal system is a challenging problem. One may compare the model-predicted joint trajectories to those measured in paraplegic subjects. This is however impractical because the model should be excited with all the stimuli that affects the motion of the paraplegics. These include, in addition to the electrical stimulation, the normal reflex activity, spasticity and voluntary contributions that could not be measured. Therefore, we only made qualitative comparisons to make sure that the model predictions are reasonable. These included special case of standing-up, such as no FES standing-up, standing-up with no arm assistance and standing-up with FES and arm forces that were in good agreement with the data reported in the literature.

8.3 Fixed-Parameter FES Controllers

Except for the FLC, the rest of the fixed-parameter controllers were adopted from the literature. These were the controllers, which because of their simplicity and practicality, have been used in the past. Coincidentally, none of these methods required a model of standing-up and could be designed easily. Since, there was no comparison of these controllers, we performed a comparative study to evaluate their performance.

The study revealed the pros and cons of each controller, the limitations of these simple controllers, and the main control problems associated with the FES assisted standing-up. Therefore, it was instrumental in our decision to adopt the machine learning techniques in the following chapters. The main results were, the necessity for nonlinear controllers, and the requirement for a coordination between the FES and voluntary control.

The conventional open-loop controllers were inefficient in applying the electrical stimulation and resulted in the high KEV. Closed-loop controllers were able to reduce the KEV but the arm forces were increased, as there was no coordination between the FES and the voluntary forces. There was a need for a controller that could not only reduce the KEV but also minimize the arm forces. This was thought to be possible only if the controller could coordinate itself with the voluntary arm forces. We evaluated the nonlinear FLC as the solution to this problem but it turned out to be very difficult to tune because it had many tuning parameters. This meant that an automated procedure was necessary to tune the parameters of the FLC to the needs of an individual subject.

8.4 Design of FES Controllers using GA

As a general-purpose optimization method, the GA was used to tune the parameters of the FLC controllers. FLC controllers were responsible for delivering the electrical stimulation to the leg muscles while the voluntary control was responsible for the control of arms. The GA was used to coordinate these two controllers to achieve similar control goals. The use of GA was preferred to the other optimization techniques because it did not require the continuous and differentiable mathematical formulations of the system and it was possible to include optimization criteria not usable with other methods. For example, in other optimization algorithms, the constraints should be expressed in terms of the optimization parameters. This excludes, from optimization, the criteria such as total time of motion, maximum joint moment or binary evaluations such as good/bad or success/failure. All of these can be handled by the GA.

The GA was capable of optimizing the standing-up motion controlled by artificial FES controller and natural voluntary control, effectively coordinating these controllers. Two FES controllers were optimized, gain-scheduling PID controller and FLC. In both cases, the number of tuning parameters were high but GA was capable of robustly optimizing the controllers for smooth trajectories and minimum arm forces. Therefore, complex controllers that are difficult to tune manually could be tuned automatically with the GA. These two applications showed the versatility of the GA, as it is applicable to almost any kind of controller with adjustable parameters.

From the point of view of the GA it does not matter if the computer model or the real subject is in the loop, i.e., it can be applied directly to the subject. However, there are important problems to consider if the GA is to be used directly in experimental setup. These are the safety of the subject and the speed of learning.

The GA starts learning with random selection of the parameters in initial generation and improves it afterward. Therefore, the initial controllers will be unsafe to try on the subjects. A solution to this problem is to limit the range of the adjustable parameters to safe regions so that all the possible solutions are safe to try. For example, we limited the control parameters so that the knee joint stimulation at initial phase of standing-up was always high and the GA was tasked to figure out the rest of the pattern. Although this slightly limited the search space, it wasn't a problem here because it was a reasonable limitation based on the expert knowledge. In arm assisted standing-up, the arms provide additional safety and will compensate for the exploratory decisions of the GA.

With the GA algorithms used here, the required number of trials for convergence was relatively high in the order of few hundred trials. Such a number of trials are inconvenient for the subjects although, they can be distributed over a period. For example, few standing-up trials can be performed a day and the GA will continue to learn and improve the controller. The high number of trials was required for the convergence of the GA to the optimal solution but the improved controllers were usually available much sooner in the learning process. From practical point of view, this is important because, there is no need to wait for the optimal solution after many trials because a working controller is available sooner and continues to improve. The learning process can also be speeded up when a computer model of the subject is available. The computer model can be used in initial stage to develop the optimal controllers for the model. The learning process then can be continued by replacing the model with the real subject. This stage will perform the necessary fine-tuning to account for the model-subject mismatch. The analysis of the sensitivity to parameter changes showed that for small model-subject mismatch, the optimized controller remained near optimal. Therefore, it might be possible to design the optimal controllers using a computer model of the subject and then use it on the real subject without considerable degradation in the optimal performance.

The GA proved to be a robust optimization method that could solve an optimization problem as difficult as coordinating the FES control to the voluntary control of the subject. It was especially appealing because the system (paraplegic subject) could be arbitrarily complex without limiting the applicability of the GA. Higher complexity may only slow the learning but could not stop it. The slowness is however, an important concern when using the GA in FES systems. Because the electrically stimulated muscles could fatigue rapidly, causing considerable changes in the system dynamics. Since, in the GA, controllers are only modified in the new generation; the inter-trial changes can not be compensated immediately. For example, if the population size is 50, after the completion of 50 trials, the new population will be produced based on the experience with the previous 50 trials.

Although the slowness of the GA in immediately compensating for the inter-trial changes is a problem for the general FES use, in the case of standing-up it can be alleviated in different ways. First, the total time of standing-up is very short and no considerable fatigue can occur. For an average two-second standing-up time, the amount of fatigue will be negligible (Kralj and Bajd, 1989). Second, a minimum waiting time can be set between the standing-up trials to minimize the effect of fatigue. Given enough time, the muscles should be able to recover from fatigue. The trials can be scheduled for few a day so that a population can be completed in few weeks. Then the GA will build the new population to be tried for the following weeks. Finally, the closed-loop FLC controllers employed here are inherently robust to disturbances. The sensitivity analysis especially showed that the controller performance to the change in muscle force is minimal as long as there is enough force left to perform the control. In a control process including GA and FLC, the GA extracts and stores in the FLC, the average behavior of the plant while the FLC executes the control and compensates for the small disturbances occurring during the operation.

8.5 Design of FES Controllers using RL

Similar to the GA, the RL is a model-free control design method capable of learning with interactions. However, unlike the GA, the RL can implement the improvements immediately, i.e., it does not have to wait for many trials to complete or even to the end of the current trial. This property is important to compensate for the effects of the internal and external disturbances. Here, a combination of the RL and FLC formed a powerful combination for learning and disturbance rejection.

The capabilities of the RL in solving the kinds of control problems unsolvable by other established control methods have made it an attractive choice for FES systems. One does not need to worry about the difficulty of modeling the FES system in detail. Because, the RL will extract, during the learning, the dynamics of the system and only those features that are important to the control objectives. This is in contrast to the model-based systems where, all the details must be modeled before a controller could be designed. As the result of these advantages, even those RL algorithms that do not have a mathematical proof of convergence have been used both in simulations and practice (Beom and Cho, 1995; Gullapalli, 1995; Howell et al., 1997). In this study, we implemented an RL algorithm capable of handling both the continuous variables and multi-agent problems. Using a simulated test problem and the model of standing-up, the algorithms were proven effective.

The RL was successful in learning the FES controllers coordinated to the voluntary control of the subject. Although, the RL is supposed to learn from success and failure, it was shown that the learning could occur only by observing the successes and without experiencing failures. Therefore, the RL can continue learning while the subject performs safe trials of standing-up. In the learning process, the RL managed to minimize performance criteria such as the arm forces and the KEV.

As with the GA, the safety and convenience of the subject during the learning trials could be improved in different ways. To ensure patient safety during the initial training phase and subsequent use of the RL controller, we envisage an initial FLC-RL controller based on reliable handcrafted rules. Fortunately, it is possible to incorporate the existing expert knowledge in the FLC in the form of control rules, which could improve the safety and speed-up the learning process. Such a handcrafted initial controller will function as "training wheels" to let the RL proceed in safety. When a computer model of the subject is available, an initial controller could be pre-trained by applying the RL algorithm to a dynamical model approximately scaled to the individual patient. The controller designed in this way could then be transferred to the real subject for further fine-tuning. This process could not only improve the patient safety but also reduce the number of the learning trials on the subject. The learning process could also be speeded-up by proper choice of the learning system structure including the learning rates of the RL algorithms, the number of the membership functions of the FLCs and the reinforcement signal. The skill to design a successful and efficient RL system is very important and usually comes with practice.

The RL-FLC combination also demonstrated good recovery from transient disturbances such as those that may be expected due to spasticity or sudden actions of the upper body and good accommodation to slow changes in the system dynamics. These changes may be expected from FES induced muscle fatigue, slow changes in the subject's physical parameters such as weight loss/gain or slow changes in the voluntary control strategy due to the patient becoming more skilled in the maneuver. The capability to adapt to the changes in the voluntary control strategy may be one of the strongest aspects of the RL opening the possibility for mutual learning. This may provide a better "cybernetic interface" in which both the subject and the RL controllers learn to cooperate to perform the maneuver better since neither the FLC-RL algorithm or the human require explicit a priori models for learning. Interaction and reinforcement is all that is needed for the mutual learning to proceed.

There are also practical advantages in using the RL compared to the other traditional controllers in that it can use any combination of sensors and actuators. Practical importance of these properties is that sensors could be located in more convenient places and there is no need to measure for example the knee angle to control it. Also there is no need to directly control the highly differentiated muscles acting on the knee joint. Instead, the nerve roots with complex response could be stimulated because, the RL is capable of finding the complex relationship between the stimulus and response even if it is not obvious to the human expert. In traditional control, such a relationship must be known in advance, i.e., the control expert should know what affects what and how.

8.6 Optimal Trajectory Generation for Standing-up

The GA, which proved as a powerful optimization method capable of handling the musculoskeletal systems, was used to generate optimal joint trajectories for impaired and abnormal cases of standing-up motion. The method was applied to the case of unassisted standing-up to identify the optimal joint trajectories and the joint torque required to execute them. This was expected to have applications in impaired standing-up in both paraplegia and functionally impaired elderly. The optimal joint trajectories tailored to the needs and impairments of an individual can be used by the conventional trajectory tracking controllers or even with more sophisticated design methods such as those described in chapter 5. It is always important to know what kind of trajectories can be followed in practice. For example, the joint trajectories of standing-up in healthy subjects are not appropriate for paraplegics and because of the weaker muscles and other impairments may not be practical or possible to execute.

The GA was able to robustly perform global optimization of the joint trajectories for different kinds of criteria such as the minimum joint torque, minimum energy, fall avoidance or a combination of them. Unlike, the majority of the optimization methods, the GA did not require the mathematical formulations of the equations of motion or the constraints in terms of the optimization parameters. This requirement limits the optimization to very simple models and excludes some forms of optimization criteria. For example, maximum joint torques can not be expressed in terms of the optimization parameters beforehand. The GA developed here, works with a simulated subject and there is no limitation on the complexity that can be incorporated into the simulation. For example, discontinuous and non-differentiable elements can be included in the simulation. The complexity can slow the GA but can not fail it. Therefore, the GA broadens the range and complexity of the optimization problems that can be solved.

The optimal movement patterns, obtained with the GA, were able to identify the optimal timing and the range of the segmental movements. For example, the extensive trunk flexion and velocity was used to minimize the loading of the ankle and knee joints. Exploration of such strategies could help to tailor the standing-up trajectories to the impairments of the subject, reduce the load on the weaker joints or set rehabilitation goals to strengthen the weak spots. Unlike, the traditional rehabilitation techniques that attempt to rehabilitate the local weaknesses, the method presented here obtains the global optimality of standing-up. Therefore, a weakness in one spot may be compensated by changing the global movement pattern that uses other available resources more effectively.

In FES assisted standing-up, optimal trajectories tailored to the physical properties and limitations of the subjects can be found before implementation of the control. It can also be used to strengthen the weak spots identified with the optimization. In functionally impaired elderly, the explored optimal strategies can be used to set rehabilitation goals or train them using, for example, biofeedback training. The latter may compare the measurement of the joint trajectories during the actual standing-up trials to the optimal trajectories and use audio-visual means to signal the subject on what is wrong and how it might be corrected. Similar techniques have already been used in the case of standing (Wu, 1997) and it might be possible to extend the technique to the standing-up motion.

8.7 Bibliography

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9 Conclusions And Recommendations

9.1 Conclusions

The research reported in this thesis involved the modeling and control of arm-assisted standing-up in paraplegia using FES. From the results of the study, the following conclusions can be made.

1. Neural network models of the voluntary arm forces during arm-assisted standing-up can be developed with reasonable accuracy. These models represent the personal strategy developed by each individual, which is different from the other patient's strategies but is consistent in one subject.
2. Although experimental evaluation is the best test for a controller, the sagittal plane model of standing-up provided an appropriate and controlled test-bed to initially evaluate and compare different control strategies. The inclusion of the closed-chain configuration and the model of the voluntary arm forces were essential in developing a realistic model.
3. Open-loop control of standing-up is both inefficient and inconvenient. Simple Closed-loop controllers improve the performance but there is more to be gained using the nonlinear and learning systems that could adapt to the specific requirements of the subject. Such controllers usually have many tuning parameters and are difficult to design manually.
4. The GA is a powerful optimization method that could be used to design complex controllers for FES standing-up. The GA's capability in successfully designing the FLC and gain-scheduling PID controllers for the given criteria showed that it can

optimize almost any parameterized controller. The GA designed controllers were superior to the similar manually designed controllers and the open-loop controllers.

5. The RL algorithm, extended to the continuous state-space and multi-agent problems, had good convergence in both the test problem and in the case of designing FES controllers for standing-up. The RL was able to compensate for the simulated disturbances and in combination with the FLC formed a robust learning system that might be able to compensate for the disturbances and time-variations in the FES standing-up.

6. The optimal trajectories for the abnormal standing-up such as those in paraplegia or functionally impaired elderly are different from those in healthy subjects and can be explored using the GA. The optimal trajectories could optimize criteria such as energy, maximum joint torque, balance or their combination. These trajectories are globally optimal for standing-up and use all the resources to compensate for the impairments and deficiencies.

With regard to the hypothesizes listed in section 1.4, the following conclusions can be drawn from the work reported in this thesis:

- Hypothesis 1 (H-1) is supported by the results in chapter 2. The accurate ANN models were developed, representing the voluntary arm forces in individuals, during standing-up.

- The model of standing-up developed in chapter 3 proved to be a valuable tool when used in chapter 4 for evaluation and comparison of different control strategies for FES standing-up. Therefore, H-2 is supported in that even a simple model is better than the experimental setup for this purpose.

- The results in chapters 5 and 6 support H-3, H-4, H-5 and H-6. Neither the GA nor RL used any information about the model of the standing-up. Both were able to achieve Man-Machine coordination and the designed FES controllers were optimal and tailored to the specifications of the subject. They were also capable of adaptation to time-variations in the dynamics of the subject.

- The results in chapter 7 support H-7. For a relatively complex model of unassisted standing-up, the GA was able to explore the compensatory mechanisms for standing-up needed by an impaired person.

Finally, the ideas in this thesis were tested on a computer model of paraplegic standing-up, which was much simpler than the reality. Therefore, one must keep in mind, the assumptions and simplifications, when interpreting the results and conclusions. As recommended in the next section, experimental evaluations are necessary to evaluate the efficiency of the proposed methods.

9.2 Recommendations for Further Research

As a logical continuation of the work in this thesis, we strongly recommend the experimental evaluation of the developed techniques. The methods can also be improved and extended to increase their efficiency. Therefore, for further research, we recommend that:

1. The neural network model of the voluntary arm forces be used in combination with the models of the lower extremities to develop realistic Man-Machine models.

2. The Man-Machine models be used in a procedure similar to that described in this thesis to design individualized controllers or in any other controller that needs the prediction of the arm forces during standing-up.

3. The neural network models developed here, which are based on the measured data from the paraplegics, be compared to the qualitative fuzzy logic models developed by the rules articulated by an expert.

4. The model of standing-up be improved by adding a foot segment, models of biarticular muscles, and a neural network model of the arm forces developed in chapter 2. These models were developed last in the program and therefore were not included in the model of standing-up.

5. The results of the comparative study of simple controllers be evaluated in experimental setup.
6. The GA be applied directly or indirectly to optimize the FES controllers for standing-up. In direct method, GA can be used on real subjects but, the indirect method applies the GA first, to a model and then transfers it to the real subject.
7. The new GA algorithms be used to improve the speed of learning. Because of the extensive research, the GA methods are improving very rapidly.
8. The RL algorithm be tested directly and indirectly to evaluate the simulation results.
9. The GA and RL methods be applied to other FES applications specially in controlling the upper extremities. Because of lesser safety concerns, they should be easier to implement.
10. The model of unassisted standing-up be extended to include muscle models. Such a model can be used to directly minimize the force of a specific muscle instead of the joint torque.
11. The optimal trajectory generation be employed to find the appropriate trajectories for the given impairment in paraplegia or functionally impaired elderly.
12. The use of optimal joint trajectories in training of the functionally impaired elderly be explored.

10 Appendix A: Equations of Motion for the Closed-Chain Model of Standing-up

D'Alembert-Lagrange principle is used to formulate the equations of motion (Paul, 1979). According to this principle, for a dynamic system to be in generalized equilibrium the virtual power must vanish. Therefore, for a multi-limb model we have:

$$\sum_{i=1}^{M}[(F_{xi} - m_i \ddot{x}_i)\dot{\tilde{x}}_i + (F_{yi} - m_i \ddot{y}_i)\dot{\tilde{y}}_i + (\tau_i - J_i \ddot{\theta}_i)\dot{\tilde{\theta}}_i] = 0 \quad \text{(A.1)}$$

Where,

M is the number of limbs.

m_i is the mass of limb i.

x_i and y_i are the coordinates of the limbs' center of mass.

θ_i is the generalized coordinate for limb i.

$\tilde{x}_i, \tilde{y}_i$ *and* $\tilde{\theta}_i$ are the virtual displacements

F_{xi} and F_{yi} are the external forces applied to the limbs' center of mass.

τ_i is the external torque applied to the joint i.

J_i is the moment of inertia about an axis passing the center of mass of the segment perpendicular to the sagittal plane.

For the given system in Figure 3.2 there are three degrees of freedom. Because, when three of the limbs are fixed in position, the position of the remaining two limbs can be determined. Choosing θ_1, θ_2 and θ_3 as generalized coordinates q_1, q_2 and q_3, the position, velocity and acceleration of the limbs can be described in terms of these generalized coordinates and their derivatives:

$$\{\dot{x}_i, \dot{y}_i, \dot{\theta}_i\} \equiv \sum_{r=1}^{F} \{U_{ir}, V_{ir}, \Omega_{ir}\} \dot{q}_r$$

$$\{\ddot{x}_i, \ddot{y}_i, \ddot{\theta}_i\} \equiv \{U_i, V_i, \Omega_i\} + \sum_{j=1}^{F} \{U_{ij}, V_{ij}, \Omega_{ij}\} \ddot{q}_j \tag{A.2}$$

Where,

F is the degrees of freedom.

U, V, Ω are functions of systems' geometry and states.

Substituting (A.2) in (A.1) results in:

$$\sum_{r=1}^{F} (Q_r - C_r - \sum_{j=1}^{F} I_{rj} \ddot{q}_j) \dot{q}_r = 0 \tag{A.3}$$

Where,

$$Q_r = \sum_{i=1}^{M} (F_{xi} U_{ir} + F_{yi} V_{ir} + \tau_i \Omega_{ir})$$

$$C_r = \sum_{i=1}^{M} (m_i U_i U_{ir} + m_i V_i V_{ir} + J_i \Omega_i \Omega_{ir})$$

$$I_{rj} = \sum_{i=1}^{M} (m_i U_{ij} U_{ir} + m_i V_{ij} V_{ir} + J_i \Omega_{ij} \Omega_{ir})$$

Equation (A.3) must hold for every possible combination of general velocities. One such a combination is:

$\dot{q}_1 = 1$, $\dot{q}_r = 0$ $(r \neq 1)$. Substitution in (A.3) results in:

$$\sum_{j=1}^{F} I_{1j}\ddot{q}_j = Q_1 - C_1$$

Similar equations can be obtained for other combinations of general velocities that can be formulated as:

$$\sum_{j=1}^{F} I_{ij}\ddot{q}_j = Q_i - C_i \tag{A.4}$$

The general formulation of D'Alembert-Lagrange principle can be applied to our model that has five members ($M = 5$) and three degrees of freedom ($F = 3$). The equations for three generalized coordinates q_1, q_2, q_3 or their counterparts θ_1 , θ_2 and θ_3 are:

$$\begin{bmatrix} I_{11} & I_{12} & I_{13} \\ I_{21} & I_{22} & I_{23} \\ I_{31} & I_{32} & I_{33} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} = \begin{bmatrix} Q_1 - C_1 \\ Q_2 - C_2 \\ Q_3 - C_3 \end{bmatrix} \tag{A.5}$$

For five unknowns ($\theta_1,\ldots,\theta_5$), (A.5) provides three differential equations. The two remaining equations are the constraint equations. The constrained equations can be obtained by considering the fact that hands and feet of the subject are fixed or the distance between them is constant. The two constraint equations are:

$$\begin{aligned} \textstyle\sum_{i=1}^{M} l_i Cos\,(\theta_i) &= v \\ \textstyle\sum_{i=1}^{M} l_i Sin\,(\theta_i) &= h \end{aligned} \tag{A.6}$$

Where, v and h are the vertical and horizontal distances between hand and foot respectively.

Five equations in (A.5) and (A.6) must be solved simultaneously to obtain the angular positions, angular velocities and angular accelerations of the joints.

10.1 Bibliography

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